# Bankruptcy prediction in Colombian case, using multilayer perceptron trained with memetic algorithm

Student:Iván Andrés Trujillo Abella,
Proffesors: Eliana María González Neira & Gabriel Mauricio Zambrano Rey

***Abstract*—Literature about Bankruptcy prediction is still incipient, therefore this work try to fill this gap by using machine learning and metaheuristics techniques to find an optimal set of weights in a MLP model.**

***Index Terms*—Machine learning, Bankruptcy, Metaheuristics, Evolutionary Algorithms, Local Search, Memetic algorithms, Neural Networks, Multilayer Perceptron.**

## I. Information(Data)

Data was retrieved from SIS by the period 2016-2019, classifying as bankrupt all Small and Medium Enterprises(SMEs) firms that were declared some process different to active or preoperative state.

To predict bankruptcy, financial ratios from one and two years before the occurrence of the event were used(in different models). For instance, for those firms that entered into a process in 2019, the financial ratios of 2018 and 2017 were used to train the models.

For those firms that did not experience the event (controls), the mean of the financial ratios was used based on their period of activity. For instance, if firm $j$ entered into database in 2017 and did not experience the event, the mean of the financial ratios for the period (2017 - 2019) was used.

### A. Exclusion criteria

- Financial information reported on a date different from December 31 of each year was excluded.
- Firms declared to be in a preoperative condition each year were excluded from the database.
- Firms that presented the event for the initial year(2016) were excluded from the database.
- Firms that present missing values and not valid financial ratios were excluded from database.

## II. Description of data

To describe categorical data, absolute and relative frequencies were used. The numerical variables were described using the mean and standard deviation if the variable is normally distributed; otherwise, the median, 25th percentile, and 75th percentile were used.

To compare the financial ratios among non-bankrupt and bankrupt firms and determine if there are significant differences among them, we used t-tests or the Wilcoxon rank sum test if the variable is normal or not, respectively. To test the normality of variables, we used the Shapiro-Wilk test. To determine if there is independence between the event and categorical variables, the $\chi^2$ test was used.

Finally, to test if there is correlation(monotonicity) among numerical variables the spearman coefficient was used.

### A. Variables (Financial ratios)

Financial ratios could be categorized in some groups, for instance *liquidity, leverage* and *profitability* for this work were used:

*1) Liquidity ratios:* Measure the firm ability to pay its financial obligations; Current ratio and Ratio of short-term liabilities were used.

*2) Profitability ratios:* Measure the firm ability to generate incomes; Gross profit margin, Net profit margin, Return on equity and Return on asset were used.

*3) Leverage ratios:* Measure the level of debt in long run; Debt equity ratio and Indebtedness ratio were used.

Were also added two classic financial ratios in bankruptcy prediction used by Altman; named in this work Altman $x_1$ and Altman $x_2$.

The Table (I) described each one of the aforementioned ratios, according to NIFF financial statements retrieved for this work.

## III. Modelling prediction

The models used to predict bankruptcy were: decision tree, logistic regression, multilayer perceptron and the proposed memetic neural network.

### A. Memetic Neural Network

Proposed algorithm...

### B. Hyperparameter tunning

To perform the hyperparameter tunning a $k = 10$ fold cross validation will be implemented, and the search of the space was by grid search.

### C. Evaluation

The total data is split in 70% to training and 30% to test, an important point is the test data will be selected in equal proportion to get a more accurate evaluation.

TABLE I: Financial ratios definition

| Ratio | Definition |
|---|---|
| Gross Profit Margin (GPM) | $\frac{\text{Gross profit}}{\text{Operating revenues}}$ |
| Net Profit Margin (NPM) | $\frac{\text{Profit(Loss)}}{\text{Operating revenues}}$ |
| Return On Equity (ROE) | $\frac{\text{Profit(Loss)}}{\text{Total equity}}$ |
| Return On Assets (ROA) | $\frac{\text{Profit(Loss)}}{\text{Total assets}}$ |
| Indebtedness Ratio (IR) | $\frac{\text{Total liabiliaties}}{\text{Total assets}}$ |
| Debt Equity Ratio (DER) | $\frac{\text{Total liabiliaties}}{\text{Total equity}}$ |
| Current Ratio (CR) | $\frac{\text{Total current assets}}{\text{Total current liabilities}}$ |
| Ratio of Short-Term Liabilities (RSL) | $\frac{\text{Total current liabilities}}{\text{Total liabilities}}$ |
| Altman $x_1$ | $\frac{\text{Total current assets - Total current liabilities}}{\text{Total assets}}$ |
| Altman $x_2$ | $\frac{\text{Accumulated profits}}{\text{Total liabilities}}$ |

TABLE II: Confusion matrix

| | Bankrupt | No-Bankrupt |
|---|---|---|
| Positive prediction | True Positive | False Positive |
| Negative prediction | False Negative | True Negative |

*1) Metrics:* The measures of performance are constructed with the table (II).

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$F1 = 2\left(\frac{Precision * Recall}{Precision + Recall}\right) - \tag{3}$$

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$$\text{Type 1} \;\; = \frac{FP}{FP+TN} \tag{4}$$

$$\text{Type 2} \;\; = \frac{FN}{TP+FN} \tag{5}$$

## *D. Balance data*

To handle the unbalanced data used undersampling.

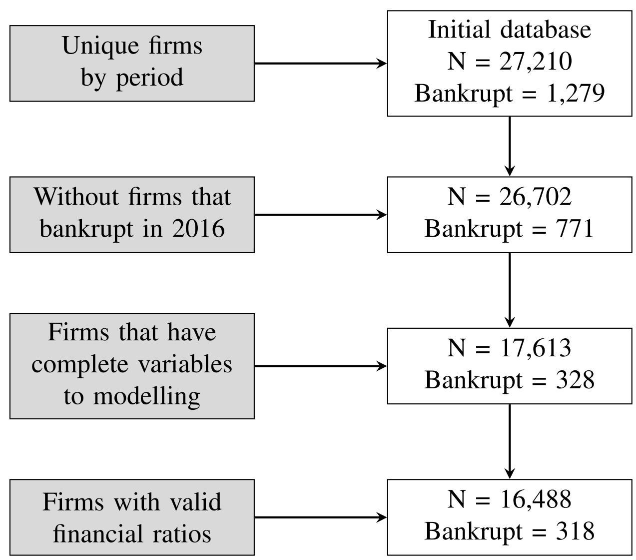
## IV. Results

From a total sample of 27,210 firms, of which 1,279 were classified as bankrupt, and after of apply exclusion criteria was obtained a final sample of 16,488 of which 318 were bankrupt.

The Figure (1) describe the process to obtain the final sample.

Financial ratios by itself no are very informative, must be exist a benchmark point, in this case we compare the level of ratios among the two groups.

Fig. 1: Flowchart processing data




The expected results are a lower level of *gross profit margin, net profit margin, return on equity, return on assets, current ration* in bankruptcy group regarding to the non-bankrupt group. Otherwise, a major level of *indebtedness ratio, debt equity ratio, ratio of short-term liabilities* in bankrupt group.

The Table (III) show the difference among the financial ratios of one year before of the bankrupt and the mean of the ratios by the period of activity of non-bankrupt firms. The results indicate that there are significance difference in all ratios, and no independence among the event and the sector.

The empirical result are coincident with the expected results. Notice that Long debt is major in the No-bankrupt group.

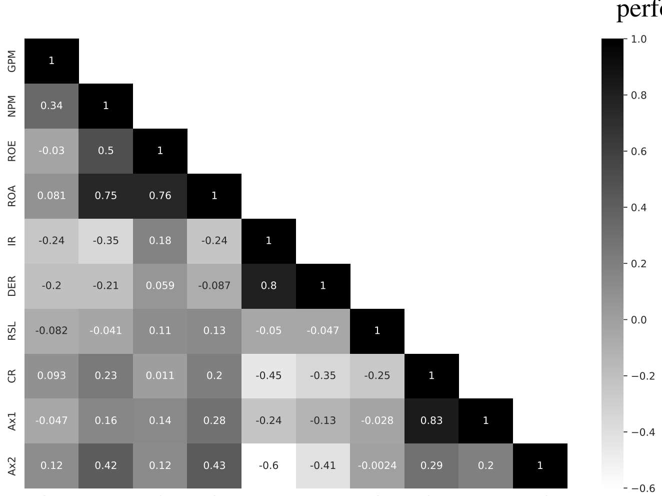
The Figure (2) show the spearman coefficient among numerical financial ratios.

The Table (IV) show us the performance of the models with

TABLE III: Year of bankrupt, financial ratios and sector among groups

| | | | | Grouped by event | | |
|---|---|---|---|---|---|---|
| | | Missing | Overall | No-bankrupt | Bankrupt | P-Value |
| n | | | 16806 | 16488 | 318 | |
| time-event, n (%) | 0.0 | 0 | 16488 (98.11) | 16488 (100.00) | | ¡0.001 |
| | 2017.0 | | 99 (0.59) | | 99 (31.13) | |
| | 2018.0 | | 96 (0.57) | | 96 (30.19) | |
| | 2019.0 | | 123 (0.73) | | 123 (38.68) | |
| GPM, median [Q1,Q3] | | 0 | 0.31 [0.18,0.56] | 0.31 [0.18,0.56] | 0.26 [0.14,0.41] | ¡0.001 |
| NPM, median [Q1,Q3] | | 0 | 0.03 [0.00,0.08] | 0.03 [0.00,0.08] | -0.02 [-0.18,0.03] | ¡0.001 |
| ROE, median [Q1,Q3] | | 0 | 0.07 [0.01,0.16] | 0.07 [0.01,0.16] | 0.01 [-0.18,0.09] | ¡0.001 |
| ROA, median [Q1,Q3] | | 0 | 0.03 [0.00,0.06] | 0.03 [0.00,0.07] | -0.01 [-0.09,0.01] | ¡0.001 |
| IR, median [Q1,Q3] | | 0 | 0.53 [0.32,0.72] | 0.52 [0.32,0.72] | 0.74 [0.59,0.88] | ¡0.001 |
| DER, median [Q1,Q3] | | 0 | 1.01 [0.40,2.25] | 0.99 [0.40,2.22] | 1.91 [0.90,4.23] | ¡0.001 |
| RSL, median [Q1,Q3] | | 0 | 0.75 [0.45,0.98] | 0.75 [0.45,0.98] | 0.53 [0.28,0.87] | ¡0.001 |
| CR, median [Q1,Q3] | | 0 | 1.70 [1.14,2.96] | 1.71 [1.15,2.98] | 1.26 [0.74,2.23] | ¡0.001 |
| Ax1, median [Q1,Q3] | | 0 | 0.22 [0.04,0.43] | 0.22 [0.04,0.43] | 0.09 [-0.08,0.28] | ¡0.001 |
| Ax2, median [Q1,Q3] | | 0 | 0.19 [0.04,0.40] | 0.19 [0.05,0.40] | 0.04 [-0.12,0.18] | ¡0.001 |
| Sector, n (%) | A | 0 | 1012 (6.02) | 990 (6.00) | 22 (6.92) | ¡0.001 |
| | B | | 282 (1.68) | 277 (1.68) | 5 (1.57) | |
| | C | | 2735 (16.27) | 2647 (16.05) | 88 (27.67) | |
| | D | | 10 (0.06) | 10 (0.06) | | |
| | E | | 28 (0.17) | 27 (0.16) | 1 (0.31) | |
| | F | | 2238 (13.32) | 2190 (13.28) | 48 (15.09) | |
| | G | | 5288 (31.46) | 5201 (31.54) | 87 (27.36) | |
| | H | | 314 (1.87) | 310 (1.88) | 4 (1.26) | |
| | I | | 363 (2.16) | 349 (2.12) | 14 (4.40) | |
| | J | | 464 (2.76) | 456 (2.77) | 8 (2.52) | |
| | K | | 474 (2.82) | 473 (2.87) | 1 (0.31) | |
| | L | | 1449 (8.62) | 1443 (8.75) | 6 (1.89) | |
| | M | | 1142 (6.80) | 1127 (6.84) | 15 (4.72) | |
| | N | | 646 (3.84) | 632 (3.83) | 14 (4.40) | |
| | O | | 4 (0.02) | 4 (0.02) | | |
| | P | | 87 (0.52) | 86 (0.52) | 1 (0.31) | |
| | Q | | 64 (0.38) | 63 (0.38) | 1 (0.31) | |
| | R | | 88 (0.52) | 86 (0.52) | 2 (0.63) | |
| | S | | 115 (0.68) | 114 (0.69) | 1 (0.31) | |
| | U | | 3 (0.02) | 3 (0.02) | | |

Fig. 2: Spearman correlation in predictor variables




the variables used to predict bankruptcy, the result indicate a lower performance to predict correctly the bankrupt firms.

The following Table (V) shows that all models have a better performance regarding to the model without balanced data.

TABLE IV: Models performance over imbalanced data

| | Logistic Regression | | Decision Tree | | Multilayer Perceptron | |
|---|---|---|---|---|---|---|
| | No-Default | Default | No-Default | Default | No-default | Default |
| precision | 0.98 | 0.15 | 0.98 | 0.06 | 0.98 | 0.00 |
| recall | 1.00 | 0.03 | 0.94 | 0.21 | 1.00 | 0.00 |
| f1-score | 0.99 | 0.05 | 0.96 | 0.10 | 0.99 | 0.00 |
| support | 4945.00 | 95.00 | 4945.00 | 95.00 | 4945.00 | 95.00 |

TABLE V: Models performance over balanced data using undersampling

| | Logistic Regression | | Decision Tree | | Multilayer Perceptron | |
|---|---|---|---|---|---|---|
| | No-Default | Default | No-Default | Default | No-default | Default |
| precision | 0.68 | 0.72 | 0.79 | 0.60 | 0.68 | 0.71 |
| recall | 0.76 | 0.63 | 0.43 | 0.88 | 0.74 | 0.65 |
| f1-score | 0.72 | 0.67 | 0.55 | 0.72 | 0.71 | 0.68 |
| support | 96.00 | 95.00 | 96.00 | 95.00 | 96.00 | 95.00 |