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Corporate Financial Evaluation and Bankruptcy Prediction Implementing Artificial Intelligence Methods

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Abstract: **-** Corporate accounting statements provide financial markets, and tax services with valuable data on the economic health of companies, although financial indices are only focused on a very limited part of the activity within the company. Useful tools in the field of processing extended financial and accounting data are the methods of Artificial Intelligence, aiming the efficient delivery of financial information to tax services, investors, and financial markets where lucrative portfolios can be created.

Key-words: - Financial Indices, Artificial Intelligence, Data Mining, Neural Networks, Genetic Algorithms

1 Introduction

The amount of accounting data quite often is extended and consist a significant disadvantage for the professional analysts or the financial experts that usually evaluate businesses. Informatics, computational neurosciences and the science of finance created original tools capable of dealing with large economic data in an effective manner. An introduction to the most recent methodologies that can be used in the financial analysis of businesses includes: a)Data Mining, b) Neural Networks, c) Evolutionary algorithms, d) Theory of the Rough Sets, e) Theory of the Fuzzy Sets, f) Multicriteria Decision Analysis g) Classical Financial Analysis.

The objective of this research is to evaluate the financial status of companies, to investigate the possibility of ex-ante preference, aiming to estimate possible future earnings or losses from investments. Artificial Intelligence methods either classify companies in known groups, with different level of risk, or cluster in homogenous sets with similar attributes. Classification with data mining techniques is compared to the initial classification by bank executives in the loan department of a Greek commercial bank, in order to verify its steadiness, through supervised training, given the initial estimations. In cases of clustering the data, initial classifications are not taken in to account, functioning non supervised training on the financial indices and on the last stage creating clusters that describe companies with identical characteristics. The processes of classification, clustering and discrimination include techniques of Artificial Intelligence-Data Mining, Hybrid methods such as Neurofuzzy Logic and Neural-genetic Networks, and finally Neural Networks, in a sample from the loan portfolio of the same bank, taking into consideration 1411 companies from different areas of activity with data from the period 1994-1997.

2 Bankruptcy Prediction- A short review of the methods

The previous articles in this area were used initially by Altman (1968) **[1]**, who elaborated the Multiple Discriminate Analysis-MDA Prediction model, Ohlson (1980) used the **–**Logit**,** Zmijewski (1984) implemented the Probit, and Statistical models as well. Lin & McClean_(2001) **[2]** elaborated methods of Discriminate Analysis, Logistic Regression & Decision Trees C5.0, Neural Networks and 1 hybrid algorithm, whilst Tung (2004) implemented a Hybrid model to amalgamate Neural Networks and fuzzy IF-THEN rules that shelf adjust fuzzy rules using learning algorithms from the neural network. Additionally Shin & Lee (2002) worked with Genetic Algorithms**,** understandable rules in paths of 1 or more variables, over which a company is considered hazardous, also Kim & Han (2003) **[3]** implemented a qualitative model on experts knowledge, evaluating qualitative and quantitative data with genetic algorithms, exports decision rules out of qualitative predictions of experts on bankruptcy. Moreover Dimitras et al. (1999) **[4]** elaborated the RST in a training set with 40 failed and 40 successful companies, whilst McKee (2003) applied a comparison of RST results with real opinions of bankruptcy prediction auditors, without significant comparative advantage of the experts prediction. Finally Beynon & Peel (2001) used the Variable Precision RST (VPRST), decision rules under possibility, partial classification inserting level of confidence and automatic discrimination FUSINTER, whilst Parks & Han (2002) implemented CBR, with measure of distance criteriacued characteristics.

2.1 Bankruptcy prediction – Results
Those researchers reported the following results by their methodologies: Altman (1968) **[1]** noticed that bankruptcy prediction is a longterm process where the financial data should include warning signals on the coming bankruptcy. The same point shared also Ohlson (1980) and Zmijewski (1984). Lin & McClean (2001) **[2]** had better results in Neural Networks and Decision Trees for human judge and ANOVA. Tung (2004) had a return of 93% in current accounting statements: 85% in statements 1 year before and 75% for 2 years before. Shin & Lee (2002) reported a return 80%, Kim & Han (2003) **[3]** with Genetic Algorithm Rules offered higher prediction precision than Neural Networks and Inductive Learning. Also Dimitras et al. (1999) **[4]** received results with Discriminate Analysis were better than Logit. McKee (2003) concluded on the excistence of Non important comparative advantage of researchers prediction. Beynon & Peel (2001) elaborating a comparison of VPRST results to the Multiple Discriminate Analysis, Logit Analysis, Decision Trees of Repeated Segmentation, Elysee ordinal discriminate, whilst the optimal was VPRST. Finally Parks & Han (2002) with AHP/CBR yielded higher than net CBR, CBR regression and logit CBR.

3 Proposed methodology
The software that implemented the AI methodologies were: Data Mining **[5]** deploying Neural Networks (*WEKA 3.0*) **[6]**, Hybrid Systems (*NEFCLASS 2.4*) **[7]**, Neurofuzzy Logic (*DataEngine 4.0-Fuzzy C-Means*) **[8]**, Neural-genetic Networks (*Neurosolutions 4.3*) **[9]**. Data came by the following 16 financial indices: 1) EBIT/Total Assets, 2) Net Income/Net Worth, 3) Sales/Total Assets, 4) Gross Profit/Total Assets, 5) Net Income/Working Capital, 6)Net Worth/Total Liabilities 7)Total Liabilities/Total assets, 8) Long Term Liabilities /(Long Term Liabilities + Net Worth), 9)Quick Assets/Current Liabilities 10)(Quick Assets-Inventories)/Current Liabilities, 11)Floating Assets/Current Liabilities, 12)Current Liabilities/Net Worth, 13) Cash Flow/Total Assets, 14)Total Liabilities/Working Capital, 15)Working Capital/Total Assets, 16) Inventories/Quick Assets, and a 17 index that included the initial classification which was done by bank executives. These methods elaborate classifications on companies which are evaluated according to their initial classifications. Test set was 50% of overall data, and training set 50% as well. Clustering is elaborated when initial classifications are ignored.

3.1 Principles and Theoretical Substratum of Methodologies

3.1.1 Data Mining
3.1.1.1 WEKA 3.0
WEKA 3.0 is a collection of machine learning algorithms for data mining either in Java or in direct implementation to data **[6]**. This platform was created in Waikato University of New Zealand. WEKA 3.0 **[7]** elaborates data preprocessing, classification, regression, clustering, it provides the user with correlation rules, visualizing them. It creates new rules of machine learning, including a variety of transformation tools of the data sets, providing the proper environment to compare learning algorithms.

3.1.2 Hybrid Methods
3.1.2.1 Neuro-Fuzzy system - NEFCLASS 2.4
NEFCLASS 2.4 is a neuro-fuzzy system based on a genetic fuzzy Perceptron of 3 layers that classifies data **[7]**. It is trained with patterns, each one of which belongs to a specific category. It detects fuzzy rules scanning data and optimizing these rules by learning the parameters of the fuzzy set that are used to segment the area of the incoming variables (features of patterns) **[10]**. Having completed the learning procedure NEFCLASS is capable of classifying new unknown data. The system can be interpreted with fuzzy IF-THEN rules. User is allowed to acquire additional information on the data, with a smaller and possibly better solution.

3.1.2.2 Neurofuzzy system Fuzzy C-Means, DataEngine 4.0
The platform DataEngine 4.0 **[8]**, extracts hidden information from raw data implementing each of the methods: Fuzzy Rule Base, Multilayer Perceptron, Fuzzy C-Means, Fuzzy Kohonen Networks, and Kohonen Networks. The elements of Fuzzy Clustering are a combination of clustering processes that belong to algorithmic methods of data analysis, and fuzzy sets. Usually a classifier results from: Iterative clustering, Agglomerative hierarchical clustering, Divisive hierarchical clustering **[11]**.

3.1.2.3 Neural-genetic Nets, NeuroSolutions 4.3

NeuroSolutions 4.3 implements every each stage in the process of developing a neural network **[10]**. It builds, it imitates, it evaluates, it extends, it exports and finally applies a neural network. The simulations are in real time with data that flow in the network, their responses, the weights adaptations, learning curves, while the total dynamics of networks and the dynamics of learning are separated in local rules of interaction. Configuration of prototype is supported with extensive number of examination tools, different from the standardised graphic representations, because prototypes are dynamic and function in real time with simulation. To optimize the generations of solutions they operate a genetic algorithm **[12]**.

4. Results from Classification methods

4.1.1 WEKA 3.0

In this machine learning platform the optimal technique was AdaboostM1 with 655 correct classifications on the test set (95,77%), 51 missclassified companies, Mean Absolute Error 0.0749, Root Mean Square Error 0.2225, RMSE 25.53% and the confusion matrix was, for the 706 companies of the training set:

Table1

	0	1
0	578	28
1	23	77

4.1.2 NEFCLASS 2.4

The misclassified companies here were significantly high at 480 cases, whilst the correct classifications were 225 a rate of 31.91%. Thus the method could not be considered as accurate. The confusion matrix was:

Table 2

	0	1
0	217	0
1	463	8

4.1.3 NeuroSolutions 4.3

The neural network implemented a genetic algorithm during each step of the training process, thus a hybrid neuro-genetic network was the outcome from this methodology. The optimal neuro-genetic hubrid used a Jordan Elman architecture for the 1 layer neural network and genetic algorithms for each repetition on the training level, with Mean Square Error 0.029, NMSE 0.113, Correlation 0.96 percentage error 6957795.5, AIC 12.618, MDL –6.39. The outcome of the training process for the 706 companies of training set was the following confusion matrix.

Table 3

	0	1
0	100 (%)	0(%)
1	0(%)	100(%)

4.2 Results from Clustering methods

4.2.1 WEKA 3.0

In the results the best solution was EM with percentage 100% of successful clusters, the second better was Farthest First with 99%, the Simple k Means followed with 86% and finally the MakeDensityBasedClusterer with 78% in the field 0 of control set. The analytical presentation of clustering Results with the training set as a 50% of overall data and control set a 50%. Where the Log likelihood was -126,7497

Table 4

Distinct Measure. of Estimator	Clustered	Instances
528,144	706 (100%) 0	(0%)

4.2.2 DataEngine Fuzzy-C-Means

Final clusters:

Cluster A: Middle Financial Position-Low Liquidity 531 companies as 0, rate 0.377 and 188 companies as 1, rate 0.1332

Cluster B: Loss Making-Limited Financial Capacity 75 companies as 0, rate 0.0531 and 2 companies as 1 - percentage 0.0014

Cluster C: Team of - Loss Making-Very Low Obligations 236 companies as 0, rate 0.1672 and 11 companies as 1- 0.0077

Cluster D: Team of - Financial Health-Middle Position 237 companies as 0 rate 0.1679 and 10 companies as 1- rate 0.0070

Cluster E: Team of - High Loss-Low Liquidity 133 companies as 0- rate 0.094 and 7 companies as 1 rate 0.0049

The number of final clusters are 5 while the banking executives gave 2 teams, that is to say the system diagnosed certain enterprises presenting peculiar behaviour and created separate clusters. The percentages of clustering concerning the initial 2 sets of classifications show an almost equal distribution of healthy companies estimated as parts of clusters C, D where are companies of medium abilities with light losses, clusters B, E with companies of significant losses have very low percentages of companies with initial classification as healthy. Regarding companies that were characterized by the banking executives as type 1, with problems, it is concluded that the small sample from this type of companies in the initial 1411 caused this very small distribution in the teams. Initial sample is not equally distributed, in companies' categories, consequently results will present this small distribution.

4.3 Comparison of evaluation methods

Implementation of Artificial Intelligence was undergone by software packages each one of them with a completely different theoretical background and philosophy of resolution, while training process in each system used either supervised or unsupervised training. Supervised training uses Classification on the data having already acquaintance on the initial classification from the bank executives, thus provides a more precise analysis. Unsupervised training ignores initial classification and evaluates data creating clusters of homogenous characteristics. Thus a comparative analysis of the output takes place in the following. The results per methodology of education were: Jordan Elman architecture for the 1 layer Neural Network and genetic algorithms for each repetition on the training level, with Mean Square Error 0.029, NMSE 0.113, Correlation 0.96 percentage error, AIC 12.618, MDL –6.39. The outcome of training process to the 706 companies was:

Table 5

	0	1
0	100 (%)	0(%)
1	0(%)	100(%)

Table 6. Classification

	Correct Class.	Misclass.	Mean Absolute Error	Rel. Abs. Error	A→A a=1.0	A→B b=2.0	B→A	B→B
WEKA 3.0 AdaBoostM1	655 (95,77%)	51	0,0749	28,53%	578	28	23	77
NEFCLASS 2.4	225 (31,91%)	480	196147,27		217	463	0	8
Neurosolutions 4.3 Jordan Elman 1 layer			6957795.5		100	0	66,66	33,3

Table 7. Clustering

Method	Distinct Measures of Estimator	Clustered	Instances
WEKA 3.0			
EM	528,144	706 (100%)	0
DataEngine 4.0 – F C M		1212 (85,89%)	218(15,45%)

The outcome of neurofuzzy methodology Fuzzy C Means was the following clusters:
Cluster A: Middle Financial Position-Low Liquidity 531 companies as 0, rate 0.377 and 188 companies as 1, rate 0.1332
Cluster B: Loss Making-Limited Financial Capacity 75 companies as 0, rate 0.0531 and 2 companies as 1 - percentage 0.0014
Cluster C: Team of - Loss Making-Very Low Obligations 236 companies as 0, rate 0.1672 and 11 companies as 1- 0.0077
Cluster D: Team of - Financial Health-Middle Position 237 companies as 0 rate 0.1679 and 10 companies as 1- rate 0.0070
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Globally there were 85,89% companies as 0 and 15,45% companies as 1. WEKA 3.0 offered the results of clustering in short time interval, with low calculating effort (other programs were also running in parallel Win XP). DataEngine 4.0 - F C M had higher complexity during application, and export of clustering results, a task that lacked to support.

5. General Conclusions

Methods of Neural Networks had high values of calculating precision with quite fast convergence, but they spent enormous time periods for training when the network had extended topology or made use of Genetic Algorithms for optimisation of intermediary solutions. Classification functioned in most cases satisfactorily, whilst it was obvious that Hybrid methods have higher possibilities in speed, with relative inferior precision regarding the percentages of correct classifications. The final confusion matrix does not provide analytical details for each individual company, restricting its application in high precision analyses. Future research could extend the accuracy of results, giving more detailed analysis.

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