Bankruptcy Prediction Using Artificial Immune Systems

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Abstract. In this paper we articulate the idea of utilizing Artificial Immune System (AIS) for the prediction of bankruptcy of companies. Our proposed AIS model considers the financial ratios as input parameters. The novelty of our algorithms is their hybrid nature, where we use modified Negative Selection, Positive Selection and the Clonal Selection Algorithms adopted from Human Immune System. Finally we compare our proposed models with a few existing statistical and mathematical sickness prediction methods.

Keywords: immune system, artificial immune system, positive selection, negative selection, clonal selection, accounting variables, bankruptcy, sickness prediction.

1 Introduction

The vertebrae Immune System (IS) is a highly complex system which is tuned to the problem of detecting and eliminating infections. The main task of the Immune System is to detect any foreign infectious element (antigen) and trigger an immune response to eliminate them. The immune system generates antibodies that detect and eliminate these antigens. This problem of detecting antigens is often described as a problem of *distinguishing between the "self" and the "non-self"*, where we describe a "self" to be synonymous to that cell that it is not harmful for the body, while a "non-self" is one which is harmful for the body and which should be destroyed [12, 13].

If one concentrates on the problem of bankruptcy prediction from a set of companies in a given environment, then sick companies can be considered as the antigens that need to be detected in the system. Many statistical models have been proposed which take into account some financial ratios or accounting variables whose values apparently demonstrate good predictive power. Most models take a linear combination of these variables to arrive at a “score” or a probability of bankruptcy in the near future, giving higher weightage to those ratios that are believed to possess higher discriminating power.

Due to the popularity of some financial ratios amongst analysts, they have widely been used for predicting the health of a company, with no proof of their superiority as an evaluating criterion. Professional attitudes and practice in this area are dominated by ‘conventional wisdom’ rather than scientific theory [11].

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Statistical models may not prove to be reliable under every circumstance. There is no single model which is equally reliable for all economic environments in which companies exist. A model prepared for sickness prediction of private companies may not accurately predict sickness of a public company [6]. Similarly a model prepared using data of companies in the United States may not accurately predict sickness of companies in India, the economic structure of these two countries being very different. Hence there is a need for a model which is flexible enough to incorporate environmental variability.

We propose a methodology for modeling an Artificial Immune System (AIS) for sickness prediction of a company. A set of accounting variables are used to represent a company. The values of these set of ratios provide a unique *signature* of a company – it is the property of the company and each company will have a different signature. This signature can be used to classify companies in the AIS context as either self or non-self.

We have selected a sample consisting of both sick and non-sick *Indian* companies, status known *a priori*. This is used for both training (generation of detectors), and validation of our model.

2 Statistical Methods in Sickness Prediction

The history of credit scoring model dates back to the seminal work of Altman [1], where the author uses Multivariate Discriminant Analysis to arrive at a linear combination of five financial ratios, called the Z-score, for predicting whether a company is credit worthy or not. Following Altman′s [1] work, many different models have been proposed, like Altman *et al.* [2, 3], Ohlson [14], Zavgren [15], Zmijewski [16], and Griffin and Lemmon [10].

For all these models the underlying notion has been to use the different accounting and financial figures to arrive at a score or a probability of failure. Depending on the score or the probability of failure we arrive at a decision whether a particular company is doing well or not and whether it is credit worthy or not.

2.1 Altman’s Z-Score

Altman [1] proposes a quantitative metric, called the Z-Score, for predicting the bankruptcy or sickness of industrial companies in USA. The author considers a sample of sixty-six corporations divided equally into two groups – bankrupt and non-bankrupt. Using twenty-two financial variables (which were important in prediction the financial performance of any corporate) for the period 1946-1965, Multivariate Discriminant Analysis was carried out to arrive at the Z-Score, the formula for which is:

$$Z = 1.2*X_1 + 1.4*X_2 + 3.3*X_3 + 0.6*X_4 + 0.999*X_5 \tag{1}$$

where,
Z = Overall Index
X_1 = Working Capital/Total Assets
X_2 = Retained Earnings/Total Assets
X_3 = Earning before Interest and Income Tax/Total Assets

X_4 = Market value of Equity/Book value of Total Liabilities
X_5 = Sales/Total Assets

Apart from the above mentioned general formula for the Z-Score, variants of the score have also been modeled for two different types of companies, namely the public industrial companies and the private industrial companies.

2.2 ZETA™–Score[1]

The ZETA™-Score proposed in [2] is a modification of the Z-Score. Changes in accounting standards and government rules regarding bankruptcy, and focus on much larger firms led to this modification. The different variables which were considered to be important for calculating the ZETA™-Score are:

1. X_1 = Return on Assets (ROA) = EBIT/Total Sales
2. X_2 = Stability of Earnings. It measured the normalized standard error of estimate in X_1
3. X_3 = Debt Service = Interest Coverage Ratio = EBIT/Total Interest Payments
4. X_4 = Cumulative profitability = Retained Earnings. It gives a picture about the of the age of the firm, about the dividend policy of the firm and about the profitability of the firm over time
5. X_5 = Liquidity = Current Ratio = (Current Assets/Current Liabilities)
6. X_6 = Capitalization = (Common Equity/Total Capital)
7. X_7 = Size = $\log_e$(Total Assets)

2.3 O-Score

The prediction models developed till 1980 did not consider the probabilistic nature of operations of corporate, hence the element of uncertainty was absent in all the models. To incorporate the concept of probability in formulating the bankruptcy prediction scores Ohlson [14] put forward the following score, called the O-Score:

$$O = -1.32 - 0.407*Y_1 + 6.03*Y_2 - 1.43*Y_3 + 0.076*Y_4 - 2.37*Y_5 - 1.83*Y_6 + 0.285*Y_7 - 1.72*Y_8 - 0.521*Y_9 \quad (2)$$

where,
O = Overall Index used to calculate the probability of failure
Y_1 = log(Total Assets/GNP Price Index)
Y_2 = Total Liabilities/Total Assets
Y_3 = Working Capital/Total Assets
Y_4 = Current Liabilities/Current Assets
Y_5 = One if total liabilities exceeds total assets, zero otherwise
Y_6 = Net Income/Total Assets
Y_7 = Fund from Operations/Total Liabilities
Y_8 = One if net income was negative for the last two years, zero otherwise
Y_9 = ((Net Income (t) - Net Income (t-1)/|Net Income (t) - Net Income (t-1)|)
t = current year

[1] This is a proprietary model for subscribers to ZETA Services, Inc. (Hoboken, NJ), so the detailed model is not presented here.

2.4 Emerging Market (EM)-Score

Due to increasing globalization and more international trade and commerce, it became imperative to include the effects of countries, foreign currencies, industry characteristics, environment, political climate, economic climate, lack of credit experience in some economies etc., in formulating the sickness prediction scores. This resulted in the EM-Score model [3].

$$\text{EM-score} = 6.56(X_1) + 3.26(X_2) + 6.72(X_3) + 1.05(X_4) + 3.25 \tag{3}$$

where,
X_1 = working capital/total assets
X_2 = retained earnings/total assets
X_3 = operating income/total assets
X_4 = book value of equity/total liabilities

3 Data Collection

The sample consists of two groups of companies, viz. the bankrupt and the non-bankrupt manufacturing units. The bankrupt group consists of companies that file a petition under the Sick Industrial Companies (Special Provision) Act 1985 at the Board for Industrial & Financial Reconstruction (BIFR)[2] India. There was no restriction placed on size of the company to be selected for our dataset, but only those were considered for the experiment for which all the data required was available and consistent.

The data collected for all companies was taken from Prowess, Indian Corporate Database, provided by CMIE[3]. This database consists of the data for all those companies that are listed either on Bombay Stock Exchange (BSE)[4] or on National Stock Exchange (NSE)[5].

Data was collected over three years – 2002 to 2004. In our data set, the non-bankrupt group for each year consists of those companies which did not file a sickness petition between 2003 and 2006. The year of bankruptcy of a company was taken to be the year when it first filed the petition, and the data of bankrupt group was dated one financial year prior to the date of filing of bankruptcy (see Table 1).

Table 1. Description of data set

Year	Total No. of Companies	No. of companies in non-bankrupt group	No. of companies in bankrupt group
2002	126	94	32
2003	147	98	49
2004	144	121	23

[2] http://www.bifr.nic.in/
[3] http://www.cmie.com/
[4] http://www.bseindia.com/
[5] http://www.nseindia.com/

4 An Artificial Immune System for Sickness Prediction

An AIS system is designed for distinguishing between self and non-self entities. In the sickness prediction context, the *self* is defined as a financially healthy company, while the *non-self* is defined as a company that is sick. The AIS maintains a set of *detectors* for recognizing *non-self* companies.

In literature different algorithms can be found that have successfully been used to engineer AIS. Some of these are the *negative selection* [9], *positive selection* [7], and the *Clonal selection algorithm CLONALG* [8]. Some attempts have been made for the bankruptcy prediction and the bond rating of companies using the negative selection algorithm [4].

We have attempted to use the hybrid of these algorithms to engineer our Artificial Immune Sickness Prediction System. This is discussed below in detail.

4.1 Development of the Model

Antibodies, Antigens, and Detectors. The set of non-bankrupt companies in our training set serve as the self set, while the bankrupt set are treated as antigens/non-self. Using these two data, a set of antibodies/detectors is generated, which will be used for classifying the test data as either sick or non-sick.

In our study an antibody is represented as a string of G elements. Each element is a real-valued financial variable. These variables and the string length may be varied according to different economic scenarios. The same scheme is used for representing self and antigens.

Matching Function. The matching of a self or an antigen with the generated detector is done by calculating the Euclidean distance between them. It is done by using the following formula:

$$e = \frac{1}{\sqrt{G}} \sqrt{\sum_{g=1}^{G} \left(\frac{x_g - y_g}{range_g} \right)^2} \quad (4)$$

$$range_g = max_g - min_g \quad (5)$$

Where,
x = the self/non-self, represented as $\{x_1, x_2 \ldots x_g \ldots x_G\}$;
y = the detector, represented as $\{y_1, y_2 \ldots y_g \ldots y_G\}$;
G= number of elements in the string

Many other distance measures can be found in literature [5]. However, our model is fairly simple: it uses real-valued representation, there is no overlap between the elements of a string, and the data can be ordered according to their value. Hence, and for simplicity, the Euclidean distance measure has been used effectively in our model without introducing any unintended bias.

4.2 Algorithms and Procedures

The AIS algorithms that we use in our model build upon the *negative selection*, *positive selection* and the *Clonal selection algorithm CLONALG*. We have used these basic algorithms as the building blocks of our procedures.

We have divided our work into two phases viz. *training* of the system, i.e., generation of the detector set, and *monitoring* or classification of test data.

Our basic procedure (Procedure-1) for training uses the negative selection algorithm to generate the detector set, which will be used for classifying test data. We further refine the detector set using either positive selection or clonal selection (Procedure-2 and Procedure-3). Finally, we compare the performance of these three procedures.

The negative selection algorithm [9] (Table 2) takes as input a set of *self*-strings that define the set of healthy companies in our application, and generates *n detectors* that are not capable of recognizing any self-string. To achieve this, random strings are generated and matched with each self-string to get the Euclidean distance. If a mismatch occurs, i.e. the distance when matched with *all* self-strings is greater than the cross reactivity threshold, *r*, the random string is taken to be a detector.

The positive selection algorithm [7] (Table 3) takes as input a set of strings M, and matches them against a set of *non-self* strings, *NS*. If a match occurs, i.e. the distance when matched with *any* self-string is lesser than the cross reactivity threshold, *r*, the random string is selected for the optimized set *A*. The rest of the strings in *M* are rejected.

Table 2. Negative Selection Algorithm

Algorithm: Negative Selection

Input: self set *S*, cross reactivity threshold *r*, no. of detectors required *n*, and length of string *L*
Output: Detector Set *A*

```
Begin
        j ← 0
           While j <= n do
                 m ← random(1, L)
                 for each s of S do
                        dis ← match (m, s);
                        if dis >= r then
                               insert (A, m)
                               breakFor
                        endif
                 endFor
                 j ← j+1
        endWhile
        return A
end
```

Table 3. Positive Selection Algorithm

```
Algorithm: Positive Selection
Inputs: set of non-self strings NS, cross-reactivity threshold r2, string-
        set M to be optimized
Outputs: optimized set A
Begin
        for each m of M do
                for each ns of NS do
                        dist ← match (m, ns);
                        if dist <= r2 then
                                insert (A,m)
                                breakFor
                        endif
                endFor
        endFor
        return A
end
```

Procedure 1: This procedure is *based* on the basic negative selection algorithm alone for generating the detector set. The self-set is the set of non-bankrupt companies for a given year and each detector has the property that it is unable to detect *at least* one self-string within the cross-reactivity threshold.

Procedure 2: Here we use a hybrid of the negative selection and positive selection algorithms. In this procedure, the detector-set generated by the negative selection algorithms is further refined by ensuring that each detector is able to detect at least one non-self-string used for training the system.

Procedure 3: Similarly, a hybrid of negative selection followed by clonal selection algorithm can also be used to refine the detector set.

5 Experiments

The above-mentioned procedures were tested using simulations on Matlab 7.0.1. For representing each company, we have taken nine financial ratios which have been shown to represent the state of a company with high fidelity [11, 16]. These ratios are the most commonly used balance sheet ratios used in current bankruptcy prediction systems. The values of these ratios are normalized between 0 and 100 to increase the precision while matching.

The data collected was partitioned into two – the training set and the test set. The details of the data set, parameters and experimental results are discussed below.

5.1 Test Sets

We used 30 companies from the non-bankrupt group and 15 from our bankrupt group as the self-set and non-self-set respectively for training our model for each year. The

Table 4. Test sets

Year	Total No. of Companies	No. of companies in non-bankrupt group	No. of companies in bankrupt group
2002	96	64	32
2003	127	68	49
2004	124	91	23

remaining non-bankrupt companies and all of the bankrupt companies were used as the test set. The characteristics of the test set are described in Table 4.

5.2 Parameters

There are three parameters that must be chosen – the number of detectors in the detector set, n, the cross-reactivity threshold for negative selection, r_1, and the cross-reactivity threshold for positive selection, r_2.

We have chosen n to be 100 for procedure-1 and 300 for procedure-2. The rationale behind taking a larger number for procedure-2 is that the optimized set after positive selection algorithm contains less than half the original number of detectors.

The r_1 and r_2 values must vary between 0 and 100 since the values of each string element is normalized on this scale. For choosing the optimum value, we conducted exhaustive tests for each possible combination of these two parameters on the 2004 data-set. For each test we computed the Type-I (8) and Type-II (9) errors for the following hypothesis:

$$H_0 = \text{All the companies detected by the detector set are bankrupt} \tag{6}$$

$$H_1 = \text{No companies detected by the detector set are bankrupt} \tag{7}$$

$$\begin{array}{c}\text{Type-I}\\ \text{Error}\\ \text{percentage}\end{array} = \frac{\text{number of bankrupt companies not classified as bankrupt}}{\text{total number of bankrupt companies}} \tag{8}$$

$$\begin{array}{c}\text{Type-II}\\ \text{Error}\\ \text{percentage}\end{array} = \frac{\text{number of non-bankrupt companies classified as bankrupt}}{\text{total number of non-bankrupt companies}} \tag{9}$$

We chose five r_1 - r_2 combinations for which the average sum of Type-I and Type-II error was the minimum for further analysis.

5.3 Results and Discussions

For each of the five r_1 - r_2 combinations chosen above, we performed 20 sets of 1000 runs each for the three data sets corresponding to the three years. These experimental runs were done for both procedures-1 and -2. We again computed the Type-I and

Type-II errors, as mentioned above, and found the average and the standard deviation of the sum of these errors for the 20 sets, averaged over the 1000 results.

Our results shown in Table 5 & 6 are for the best r_1 - r_2 combination, that came out to be r_1=47 and r_2=30.

Table 5. Classification results for procedure-1 with r_1=47 and r_2=30

Year	Type-I Error (%)		Type-II Error (%)	
	average	St. error	average	St. error
2002	0.01890	0.00845	39.8175	0.47202
2003	11.3277	0.33707	1.75147	0.02333
2004	3.8786	0.25307	2.71593	0.04419

Table 6. Classification results for procedure-2 with r_1=47 and r_2=30

Year	Type-I Error (%)		Type-II Error (%)	
	average	St. error	average	St. error
2002	0	0	25.1207	0.221
2003	5.4432	0.0902	1.5318	0.0099
2004	0.0943	0.028	3.0158	0.03788

Upon examination of the above results, we can conclude that the results obtained through procedure-2 exhibit higher accuracy rates than those obtained by procedure-1, consistently for all the years. Thus we can claim that by using positive selection for improving the detector set, the overall classification accuracy can be enhanced.

We observe a marked difference between the accuracy achieved in 2003 and 2004, and that achieved in 2002. This difference can be attributed to the fact that the non-bankrupt groups for 2003 and 2004 did not contain any company that filed for bankruptcy over a span of three years – i.e. the non-bankrupt group for a particular year contains companies that had maintained a good record for at least three consecutive years. This was not possible for the year 2002 due to unavailability of data for the years 2000 and 2001. In spite of this shortcoming, there is a significant improvement in the accuracy level of the results obtained for year 2002 through using procedure-2 over those obtained by using procedure-1.

5.4 Comparison with Other Sickness Prediction Models

To compare our test results obtained above we classified our data set using three statistical methods viz. the Altman Z-score , the Emerging Market score, and the Ohlson Score, and then calculated the errors for the classification results obtained.

It can be seen from Table 7 that for the year 2002 the accuracy of our AIS classification is far better than any of the results obtained by both the statistical methods. For the other two years our Type-1 error percentage is slightly higher than that of the Z-score. As far as the Type-II error rate for all the three years is concerned, both our proposed models always yield far better results than the Z-score model.

Upon comparison of the result of our AIS models with the EM-score results, we can see that although we have obtained a slightly higher Type-II error, we obtain a marked improvement in Type-I error rate.

Table 7. Classification results obtained by statistical models

Year	Z-score		EM-score	
	Type-I Error (%)	Type-II Error (%)	Type-I Error (%)	Type-II Error (%)
2002	9.375	36.56	53.125	0
2003	4	39.79	32.653	0
2004	0	43.8	30.434	0

The O-score results are not shown as it classified all the companies in our dataset as bankrupt giving a probability of bankruptcy for each one of them to be greater than 0.5.

The high error obtained in classification by the statistical methods can be attributed to the fact that these methods have constraints on the size, market and the economic environment of the companies which are not imposed in selection of our dataset.

6 Conclusion and Future Scope

In this paper, we explored the possibility of using the Artificial Immune Systems framework for predicting the sickness of a company over a period of one year. We have compared two different procedures using the basic negative selection and positive selection algorithms; and our results clearly show the advantage of using positive selection algorithms to optimize the detector set generated by the negative selection. However, both our techniques demonstrate very high accuracy.

Our method uses only two parameters, r_1 and r_2 which can be determined easily after a few simulations and statistical tests. The results, however exhibit high accuracy over a range of combinations of these parameters, regardless of the data set used for training. This offers us the opportunity of using different data sets for training depending on economic environment of the companies that we would like to classify. There is also a possibility of using more advanced distance measures or data-mining techniques for improving the detector set.

We also compared our results with classification results obtained by statistical methods and noted a marked difference in performance on the three data sets we have used.

These models can also be used for Credit Rating with slight modifications in data representation and can be easily designed to suit different economic environments by incorporating some macro-economic variables in the antigen/antibody representation.

There is also scope for finding the optimal set of financial variables to be used in our model which may exhibit enhanced results.

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