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Financial Intelligence in Prediction of Firm's Creditworthiness Risk: Evidence from Support Vector Machine Approach

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Abstract

This paper seeks to explore the usefulness of financial indicators in measuring the financial health of companies and how to use these relevant attributes to design intelligent financial solution provided to investors and financial institutions to predict financial crashes. Such indicators are of the utmost importance since financial risks have significantly increased in the context of the current global financial crisis.
Given that a company forms a micro financial system, its good financial health contributes to building a powerful economic engine; therefore, we have selected a sample of 20 firms over 3 years (2009-2011) whose 39 financial indicators are provided, and we have used Principal Factor Analysis (PFA) approach to reduce the dimension of the input matrix to 8 factors that impact on the firms' financial health, in order to set up our Support Vector Machine (SVM) Model through which we can predict firms' creditworthiness risk.

Keywords: Firm; Intelligent financial solution; Financial health; Creditworthiness; Support Vector Machine

1. Introduction

The global financial crisis of 2008 has made the management of financial risk a strategic regulatory factor, not only for bank structures but also for any financial or economic entity, regardless of its size and the sector in which it undertakes its activity.

Although many regulatory regimes have established their rules (Basel II, Basel III…) of financial risk control from the consequences of different financial crises and from their impact on the solvency of

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institutions, it is by no means easy to study and measure this key, and so there is still a long way to go in this area.

In fact, financial market regulations have appeared in the wake of the financial crises which have been recurring phenomena in the history of economy; thus, it is relevant to cite some landmark financial crashes that have occurred over the last two hundred years:

- 1974: Herstatt Bank (German) crisis caused a huge crisis in foreign exchange liquidity, and it caused several more bank failures, mainly the banks to which Herstatt Bank owed the delivery of foreign currency. The Herstatt crisis is well known in international finance as "Herstatt risk," and it had many implications for the regulatory framework [1].
- 1994: Metallgesellschaft, a German conglomerate, revealed publicly that its "Energy Group" was responsible for losses amounted to $1.5 billion, due mainly to cash-flow problems resulting from large oil forward contracts. The Metallgesellschaft crisis had many implications for the authorities which led them to explore how proper supervision could have averted disaster and how similar financial crises may be avoided in the future [2].
- 1998: the failure of Long-Term Capital Management (LTCM) is said to have nearly blown up the world's financial system. Indeed the fund's woes threatened to create major losses for its Wall Street lenders. LTCM was so big that the Federal Reserve Bank of New York took the unprecedented step to facilitate a bailout of the private hedge fund; for fear that a forced liquidation might ravage world markets [3], [4].
- 2008: the global financial crisis or global economic crisis is commonly believed to have begun in July 2007 with the credit crunch, when a loss of confidence by US investors in the value of sub-prime mortgages caused a liquidity crisis. By September 2008, the crisis had worsened as stock markets around the globe crashed and became highly volatile. The housing collapse in the US is commonly referred to as the trigger of the global financial crisis, especially with a series of banks and insurance companies' failures such as the collapse of Lehman Brothers in September 2008. It is believed that the financial system needed better regulation and required unprecedented government intervention [5].

Although it is very difficult to define the notion of risk, it is generally admitted that risk is related to a negative occurrence that is caused by external or internal vulnerabilities that we cannot predict [6].

Theoretically, we can distinguish these different risks that a financial institution can meet: Credit risk, Interest rate risk, Currency risk, Operational risk, Liquidity risk and Risk strategy.

Thus, when it comes to measuring financial risk in its entirety, the question is more complicated due to the lack of sufficient historical data as required for analysis. Since companies and banks form the micro financial system, we can focus our studies on the parameters affecting micro financial health with the purpose to develop our Support Vector Machine Model as an instrument for predicting the firm's creditworthiness risk and for helping businesses improve solvency, productivity and profitability, as well as assisting the financial institution in decision-making through the creditworthiness risk prediction.

This paper is structured as follows. Section 2 presents an overview of the creditworthiness risk. Section 3 shows detailed description of the financial indicators which reflect the creditworthiness of the company. Section 4 reviews how this relevant attributes can be used to asses and predict the firm's creditworthiness risk using the Support Vector Machine Model. Finally, the last section provides some concluding comments.

2. Creditworthiness risk

The Basel III Committee's comprehensive reform package led to the conclusion that many banks were holding insufficient liquidity buffers. During the most severe episode of the crisis, the market lost confidence in the solvency and liquidity of many banking institutions. The weaknesses in the banking sector were rapidly transmitted to the rest of the financial system and, hence, to the real economy.

A strong and resilient banking system is the foundation for sustainable economic growth, as banks are the center of the credit intermediation process between savers and investors. Moreover, banks provide critical services to consumers, small and medium-sized enterprises, large corporate firms and government who rely on them to conduct their daily business, both at domestic and international levels.

Through The Basel III reform package which builds on the three pillars of the Basel II framework, the committee aims to improve risk management and governance as well as to strengthen bank's transparency and disclosures; as such it is intended to provide an extra layer of protection against model risk and measurement of creditworthiness risk [7].

Creditworthiness risk is the uncertainty surrounding a firm's ability to service its debts and obligations. Prior to default, there is no way to discriminate unambiguously between firms that will default and those that will not. At best, we can only make probabilistic assessments of the likelihood of default.

Although these risks do not seem large, they are in fact highly significant. First, they can increase quickly and with little warning. Second, the margins in corporate lending are very tight, and even small miscalculation can undermine the profitability of lending.

But most importantly, many lenders are themselves borrowers, with the high level of leverage. Unexpected realizations of creditworthiness risk have destabilized and destroyed lenders. Banks, finance institutions, and insurers: none have escaped unscathed.

Creditworthiness risk cannot be hedged away, or structured away. The government cannot insure it away. It is a reflection of the substantial risk in companies' futures. Various schemes exist, and more are coming, which can shift risk, but in the end, someone must bear this risk. It does not "net out" in the aggregate.

The risk of firm's crash affects virtually every financial contract. Therefore the pricing of creditworthiness risk has received much attention; both from lender who have to ensure its claims and from traders who have a strong interest in pricing transactions accurately. For this purpose, it is extremely important to be able to know about the future firm's financial behavior and to assess the degree of firm's solvency. Through this; the purpose of this exercise is to find out what the financial parameter estimates tell us about the future firm's financial behavior [6], [8].

3. Financial indicators analysis

Through this study, we demonstrate the use of actual financial data for financial ratio analysis in order to show exactly how a financial institution can predict how well the financial behavior of one company will perform in comparison to of another one and how we can overcome the difficulties in applying the principles of financial ratio analysis when the data are not homogeneous as is the case in our samples.

The financial analysis is the selection and interpretation of financial data to assist in investment and financial decision-making. Financial analysis may be used internally to evaluate issues such as the efficiency of operations, and credit policies, and externally to evaluate potential investments and the creditworthiness of borrowers.

The primary source from which to draw the financial data needed is the data provided by the company itself in its annual report and required disclosures. The annual report includes the income statement, the balance sheet, and the statement of cash flows [9].

A financial ratio is a comparison between one bit of financial information and another. Ratios can be classified according to their general characteristics; in this study we have chosen the classification as follow:

- The Operating ratios: When we assess a company's operating performance, we want to know if it is applying its assets in an efficient and profitable manner. The operating ratios show the efficiency of a company's management to control the expenses of a firm and to measure its profitability and its financial soundness of a firm. We have selected:

Working Capital ratio: Indicates whether a company has enough short term assets to cover its short term debt. It measures of both a company's efficiency and its short term financial health.
Working Capital Requirement: Indicates the minimum amount of resources that a company requires to effectively cover the usual costs and expenses necessary to operate the business.
Cash ratio: It is commonly used as a measure of company liquidity. It can therefore determine if, and how quickly, the company can repay its short term debt.
Cash flow ratio: It is the cash resulting from income generating activities minus expenses and investments. It is a key metric for any entity that handles cash, and it can determine if the company can finance its operations through the cash it generates from ongoing activities.

- The financial ratios: When we assess a company's financial condition, we want to know if it is able to meet its financial obligations. It can be used to analyze trends and to compare the firm's financial situation of those of other firms. We have selected:

Productivity ratio: It represents the efficiency with which physical inputs are converted to useful outputs. It can be computed by the ratio between the value added and the turnover. This is an indicator of company's ability to harness physical and human resources to maximize its production of goods and services.
Leverage ratio: It measures how much money a company should safely be able to borrow over long periods of time. It does this by comparing the company's total debt and dividing it by the amount of owner's equity.
Coverage ratio: A measure of a company's ability to meet its financial obligations, it compares a company's total debt to its cash flow and it provides an indication of the company's ability to cover total debt with its yearly cash flow from operations.
Solvency ratio: It provides an assessment of the likelihood of a company to continue congregating its debt obligations. It compares a company's owners equity to its total assets. Generally speaking, the lower a company's solvency ratio, the greater the probability that the company will default on its debt obligations.

- The profitability ratios: Compare components of income with sales. They give us an idea of what makes up a company's income and are usually expressed as a portion of each dollar of sales. We distinguish:

Operating Profit Margin: This is a ratio that indicates how much of each dollar of sales is left over after operating expenses and it compares the operating income of company to its turnover.
Net Profit margin: This is a ratio of net income to turnover, and indicates how much of each dollar of sales is left over after all expenses.

There are hundreds of ratios that can be formed using available financial statement data. The ratios selected for our study depend on the type of our analysis about the creditworthiness and the type of our sample of firms. We will see in the next section how to use these ratios to get prediction of firm's creditworthiness risk through a Support Vector Machine Approach.

4. Support Vector Machine Model

4.1. Theoretical Model

Support Vector Machine (SVM) is a powerful method for pattern recognition and classification introduced by Vapink [10]. The SVM maps the input data into a higher dimensional feature space via a nonlinear map and construct a separating hyperplane with maximum margin. It has been proposed as a technique in times series prediction. The key characteristic of SVM is that a nonlinear function is learned by a linear learning machine in a kernel induced feature space while the capacity of the system is controlled by a parameter that does not depend on the dimensionality of the space. The following shows the SVM algorithm [11]:

Consider a given training set $\{x_i, y_i : i = 1, \cdots l\}$ randomly and independently generated from an unknown function, where $x_i \in X \subseteq R^n$, $y \in Y \subseteq R$ and l is the total number of training data.
The SVM approximates the unknown function using the following form:

$$f(x) = \langle w, \Phi(x) \rangle + b \quad (1)$$

Where $\langle , \rangle$ is the dot product, w and b are the estimated parameters and Φ is a non linear function is used to map the original input space R^n to high dimensional feature space. So, the nonlinear function estimation in original space becomes linear in feature space.
The optimization goal of standard SVM is formulated as:

$$\text{Minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \quad (2)$$

Subject to:

$$y_i - \langle w, \phi(x_i) \rangle - b \le \varepsilon + \xi_i,$$
$$\langle w, \phi(x_i) \rangle + b - y_i \le \varepsilon + \xi_i^*,$$
$$\xi_i^*, \xi_i \ge 0, i = 1, \ldots\ldots, l.$$

Where the constant $C > 0$ determines the trade off between the flatness of f and the amount up to which deviations larger than are ε tolerated and ξ_i, ξ_i^* are slack variables and they are introduced to accommodate, respectively, the positive and the negative errors on the training data. The formulation above corresponds to dealing with the so called ε-insensitive cost function:

$$|\xi|_\varepsilon := \begin{cases} 0 & \text{if } |\xi| < \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{cases}$$

This constrained optimization problem is dealt with by introducing Lagrange multipliers $\alpha_i, \alpha_i^*, \beta_i, \beta_i^*$:

$$\mathrm{L_P}(\mathrm{w}, \xi, \xi^*, \alpha, \alpha^*, \beta, \beta^*) = \frac{1}{2}\langle \mathrm{w.w} \rangle + C.\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}\alpha_i.\langle w, \phi(x_i) \rangle - y_i + b + \varepsilon + \xi_i)$$
$$- \sum_{i=1}^{l}\alpha_i^*.(y_i - \langle w, \phi(x_i) \rangle) - b + \varepsilon + \xi_i^*) - \sum_{i=1}^{l}(\beta_i.\xi_i + \beta_i^*.\xi_i^*) \quad (3)$$

By minimization the Lagrangian with respect to the primal variables we obtain:

$$w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*).\phi(x_i) \quad (3.1)$$

And $\sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0,\ 0 \le \alpha_i \le C,\ 0 \le \alpha_i^* \le C,\ i = 1, \ldots\ldots, l$

The dual problem is obtained by introducing (3.1) in (3) and it is expressed as:

$$\text{maximize } -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*).(\alpha_j - \alpha_j^*).K(x, x_i) + \sum_{i=1}^{l}(\alpha_i - \alpha_i^*).y_i - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*).\varepsilon \quad (4)$$

Subject to constraints:

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0,\ \ 0\le\alpha_i\le C,\ \ 0\le\alpha_i^*\le C,\ \ i=1,\ldots\ldots,l$$

Finally, the nonlinear function is obtained as:

$$f(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*).K(x,x_i)+b \tag{5}$$

Where $K(x_i,x_j)=\langle\phi(x_i),\phi(x_j)\rangle$ is defined as the kernel function. The elegance of using the kernel function is that one can deal with feature spaces of arbitrary dimensionality without having to compute the map Φ. Any function that satisfies Mercer's condition can be used as the kernel function.

4.2. Input factors using Principal Factor Analysis (PFA) approach

This research investigates financial data over 3 years 2009-2011, which all come from 20 Moroccan companies that belong to different sectors and have different sizes.

Firstly, we have selected 39 variables, over 3 years, which are impacting the financial health of companies:

Table 1. Selected variables.

V1	Turnover	V14	Equity / Total assets	V27	Financial costs / Gross operating profit
V2	Net equity	V15	Working capital / Working capital requirement	V28	Financial costs / Operating cash surplus
V3	Net cash	V16	Leverage ratio	V29	Gross operating profit / Turnover
V4	Net profit	V17	Coverage ratio	V30	Net profit margin ratio
V5	Working capital	V18	Change in debts / Cash flow	V31	Net profit / Net equity
V6	Working capital requirement	V19	Rotation net cash	V32	Net profit / Permanent capital
V7	Value added	V20	Inventory turnover	V33	Long term debts / Cash flow
V8	Gross operating margin	V21	Delay of payment of customers	V34	Net profit / Equity
V9	Gross operating profit	V22	Delay of payment to vendors	V35	Staff costs
V10	Operating cash surplus	V23	Gross margin / Turnover	V36	Lenders
V11	Free cash flow	V24	Cash flow / Turnover	V37	State
V12	Cash flow	V25	Productivity ratio	V38	Current operating income
V13	Solvency	V26	Staff costs / Value added	V39	Non-operating income

When we assess a firm's creditworthiness risk, we want to know if a company is solvent, if it is profitable and if it is still productive; this is why we have computed the correlation coefficients, using SPSS 10, between our 39 variables involved and the three relevant components: Solvency, productivity and profitability, in order to detect the variables that influence the most [12].

For a more thorough precision of the risk prediction, the dimensionality of the input factors can be reduced by the use of Principal Factor Analysis (PFA) approach using SPSS10, in order to obtain factors that create a new dimension and that can be visualized as classification axes along which measurement variables can be plotted [13].

As can be seen, in the following table 2, that presents 8 factors as the number of factors to be retained, instead of 39 variables. The eight factors based on the data from 2009-2010 can explain 86% of the variance contribution, which means the model has a good measuring effect. So, we can reduce the input factors dimension to eight factors to predict the crediworthiness risk.

Table 2. Input Factors.

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
V1	0,921	-0,082	0,077	0,042	-0,021	-0,050	-0,109	-0,061
V2	0,995	0,020	-0,022	-0,049	0,013	-0,008	-0,032	-0,015
V3	-0,299	0,072	-0,095	0,747	0,401	0,081	0,166	0,188
V4	0,986	-0,006	-0,023	0,073	0,061	-0,003	-0,004	0,001
V5	0,941	-0,005	-0,023	-0,135	-0,009	-0,005	-0,006	-0,012
V6	0,934	-0,016	-0,007	-0,242	-0,070	-0,017	-0,031	-0,040
V7	0,996	-0,031	-0,004	0,008	0,025	-0,013	-0,019	-0,013
V8	0,997	-0,032	0,000	-0,007	0,016	-0,015	-0,025	-0,017
V9	0,990	-0,031	-0,009	0,035	0,039	-0,010	-0,010	-0,009
V10	0,912	-0,035	-0,024	0,335	0,178	0,014	0,040	0,054
V11	0,873	-0,031	-0,030	0,404	0,201	0,026	0,063	0,077
V12	0,901	0,009	-0,045	0,362	0,211	0,019	0,045	0,070
V14	0,299	0,571	0,010	0,016	-0,076	0,194	0,263	-0,192
V15	-0,010	-0,014	0,000	0,144	-0,309	-0,179	-0,219	0,586
V16	-0,070	-0,320	-0,170	-0,266	0,521	0,488	-0,175	-0,086
V17	0,068	0,313	0,899	-0,105	0,176	0,062	0,002	0,088
V18	0,041	0,381	0,849	-0,001	0,101	-0,013	0,098	0,039
V19	-0,026	0,469	-0,066	0,351	-0,204	0,405	-0,290	-0,143
V20	-0,090	-0,091	-0,076	-0,220	0,163	-0,065	0,762	0,210
V21	0,215	0,226	-0,345	-0,067	0,139	-0,510	0,159	0,058
V22	-0,032	0,585	-0,400	-0,142	0,040	0,051	-0,133	0,273
V23	0,318	0,432	-0,384	-0,219	-0,154	0,320	0,403	0,256
V24	0,026	0,878	-0,282	-0,064	0,141	0,028	-0,150	0,001
V26	0,974	-0,030	0,016	-0,098	-0,026	-0,023	-0,056	-0,026
V27	0,920	-0,006	0,010	-0,209	-0,075	-0,021	-0,077	-0,036
V28	0,987	-0,029	-0,012	0,083	0,064	-0,009	-0,003	-0,001
V29	0,991	-0,028	-0,012	0,032	0,040	-0,009	-0,006	-0,007
V30	-0,911	0,040	-0,014	0,345	0,135	0,044	0,064	0,084
V31	-0,045	0,007	0,038	0,133	-0,020	-0,422	-0,142	-0,302
V32	-0,031	-0,736	-0,059	0,093	-0,061	0,172	-0,092	0,021
V33	0,036	-0,159	0,084	-0,130	-0,054	0,220	-0,365	0,580
V35	0,537	-0,341	0,077	-0,005	-0,309	0,351	0,242	0,175
V36	0,060	0,871	-0,277	-0,066	0,089	0,011	-0,175	-0,017
V37	0,209	0,249	0,209	0,329	-0,697	-0,159	0,115	0,066
V38	-0,024	0,085	0,023	0,165	-0,346	0,431	0,161	-0,371
V39	0,068	0,313	0,899	-0,105	0,176	0,062	0,002	0,088

4.3. SVM simulation for creditworthiness risk prediction

SVM is a new technique used for regression and classification data, but their efficiency depends in practice on an optimal selection of hyper-parameters. This hyper-parameter estimation is often called the model selection problem.

If it is applied to a large data set, however, it requires a long time for training so its performance can be degraded a long time. To speed up training thereby shortening the time for model selection, several methods have been proposed, one of which is to reduce the training set size. That is why we perform our model selection for SVM on the training data selected that is involved on the 8 factors analysis as mentioned above.

To obtain a good performance, we have carefully chosen some parameters that include the regularization parameter C, which determines the trade-off between minimizing the training error and minimizing model complexity, and parameters of the Kernel function.

In this simulation we test the classification using the kernel function RBF so two parameters need to be chosen; they are the γ width of the RBF function and the soft margin parameter C of SVM [14].

One method often used to select the parameters is grid search on the log ratio of the parameters associated with cross-validation. Value pairs (C, γ), respectively was assessed using cross-validation and then we have chosen the pair with highest precision: (C, γ) = (100, 0.1).

According to the architecture of the support vector machine, only the training data near the boundaries are necessary. In addition, because the training time becomes longer as the number of training data increases, the training time is shortened if the data far from the boundary are deleted. Therefore, we have implemented a sample of 40 Moroccan companies whose financial data is extracted over (2009-2011) and reduced on our 8 factors analysis. Then we have applied our SVM model over the training set on a new sample of 20 Moroccan companies whose financial data is selected over (2009-2011), with the purpose to measure the precision of creditworthiness risk prediction as compared to the actual data of 2011.

In order to test the effectiveness of the proposed method, a series of simulations were carried out to predict solvency, productivity and profitability, as follows:

Fig. 1. Solvency risk prediction

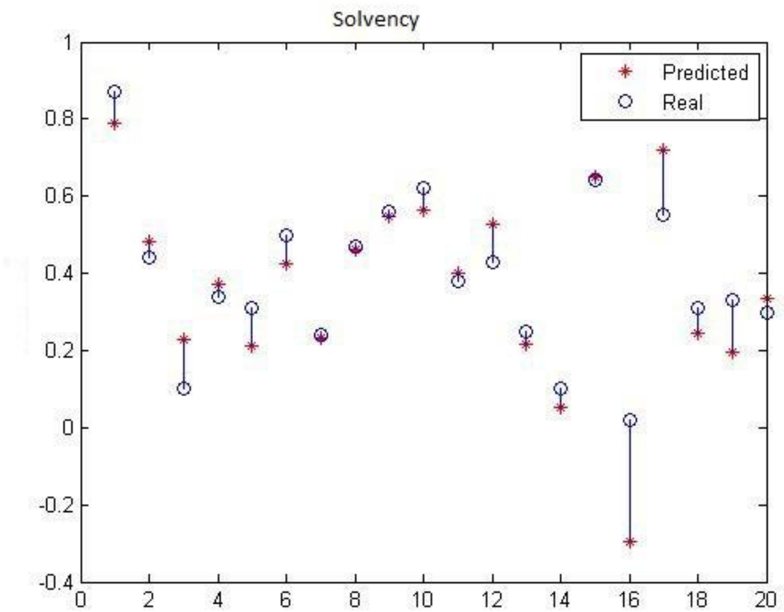


Fig. 2. Productivity risk prediction

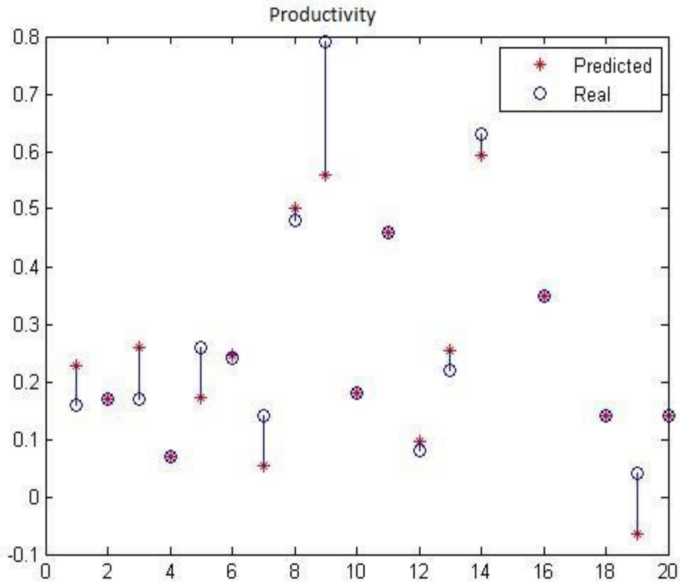
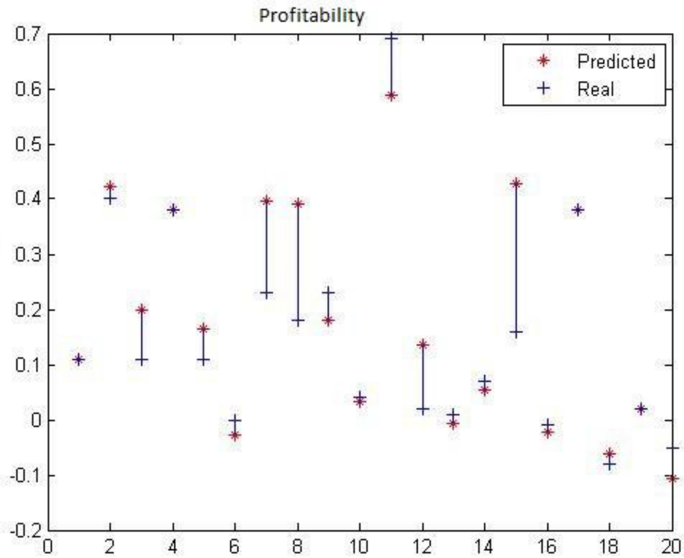


Fig. 3. Profitability risk prediction



The aim is to approximate the prediction performance based on the knowledge of the training set, as proved by the results above; the fact that the precision of the creditworthiness risk prediction is about 90%, means that the model has a good measuring effect.

5. Conclusion and suggestion

This study has selected a sample of financial data of 20 companies over 2009-2011 to measure the Creditworthiness risk through the solvency risk, the productivity risk and the profitability risk, using Support Vector Machine (SVM) Model that included eight principal factors provided from Principal Factor Analysis Model that can be used as input factors to forecast the Creditworthiness risk of a company.

The simulation results show that our SVM model gives good precisions, and that we are able to forecast the companies' default and to give intelligent financial solutions to investors and financial institutions to help them in decision-making.

In order to ensure the availability and the accuracy of data, this research discarded a number of indicators which present difficulties in acquisition or differences in the method of calculation. For example, besides information that companies are required to disclose through financial statements, other information such as securities market prices of publicly-traded corporation and information on stock price indices for industries and for the market will have a certain degree of precision constraints of measuring risk which will require further improvements .

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