International Journal of Computer Applications (0975 – 8887)
Volume 34– No.7, November 2011

Bankruptcy Prediction using SVM and Hybrid SVM Survey

Jayanthi. J
Dept of CSE
Pondicherry University
Pondicherry, India

Suresh Joseph. K
Asst. Professor, Dept of CSE
Pondicherry University
Pondicherry, India

Vaishnavi. J
Dept of CSE
Pondicherry University
Pondicherry, India

ABSTRACT
Bankruptcy prediction has been a topic of active research for business and corporate organizations since past decades. It is an effective tool to help financial institutions and relevant people to make the right decision in investments, especially in the current competitive environment. The tool provides auditors and managers a chance to identify the problems early. Thus, relevant people have an opportunity to intervene early into affairs problems to reduce the expected cost of bankruptcy failure. The primary objective is to reduce well in advance as much as possible to the loss of relevant beneficial, such as investors, managers and employees. This paper provides a survey of bankruptcy predictions using a novel machine learning approach: support vector machine (SVM) and hybrid SVM. The underlying motivation for using SVM and hybrid SVM are the ability of this methodology to determine accurate forecast bankruptcy data set when the underlying system processes are typically nonlinear, non-stationary and not defined a – priori. SVM and hybrid SVM have also been proven to outperform other non-linear techniques including neural-network based non-linear prediction techniques.

Keywords
Bankruptcy prediction and SVM

1. INTRODUCTION
The purpose of this paper is to present a general survey of Bankruptcy prediction using Support Vector Machine (SVM) and hybrid SVM. This survey is based on publications and information found in technical books and journals as well as other information data sources such as SVM technology oriented websites.

Bankruptcy prediction is a very important economic phenomenon. It is also a problem that affects the economy of a country and it can be considered as an index of the developments and robustness of the economy. The high individual, economic, and social costs encountered in corporate failures or bankruptcies have spurred searches for better understanding and prediction capability.

Bankruptcy prediction **E.L.Altman(1993), C.Pate(2002) [3, 4]** is an important and serious topic for business and corporate organizations. Prediction of corporate bankruptcy is a phenomenon of increasing interest to investors or creditors, borrowing organizations and government alike. Timely identification of organizations' impending failure is desirable. Business failure is a general term and according to widespread definition, is the situation in which a firm cannot pay lenders, preferred stock shareholders, suppliers, etc, or where a bill is overdrawn, or the form is legally bankrupt. Signs of potential financial distress are evident long before bankruptcy occurs. Financial distress begins when an organization is unable to meet its scheduled payments when projection of future cash flows points to an inability to do so in near future. The causes leading to business failure and subsequent bankruptcy can be divided into **S.Dev (1974) [5]** economic, financial, neglect, fraud, disaster and others. Economic factors include industry weakness and poor location. Financial factors include excessive debt and insufficient capital. When errors and mis-judgments proliferate, it could be a sign of managerial neglect. Corporate fraud became a public concern during late nineties. Disaster is sometimes the cause of corporate failure. It includes human error and malice.

The research of predictive model for bankruptcy prediction started in the late 1960 and still be vital to this day. One of the early work of predicting bankruptcy failure conducted by **Beaver (1968) [1]** who created a univariate discriminant model using financial ratios selected by dichotomous classification test. In addition to discriminant analysis, the traditional statistical methods include correlation, regression, logistic models **Martin (1977), Ohlson (1980) [12, 13]**, factor analysis, etc. Balcaen and **Ooghe (2006) [2]** presented an overview of the classic statistical methods for predicting business failure developed thus far and provided a detailed analysis of four types: (i) univariate analysis, (ii) risk index models,(iii) multivariate discriminant analysis, and (iv) conditional probability model(logit, probit, linear probability models). The authors identified a number of problems in the application of these methods to bankruptcy prediction which include data anomalies and data instability, inappropriate sample and independent variable selection, and ignorance of time horizon. The statistical applications, although enhanced over time, were restricted by the rigorous assumptions of traditional statistics such as the linearity, normality, independence among predictor variables and pre-existing functional form related to criterion and predictor variables. The traditional methods contain limitations in terms of effectiveness and validity.

Now bankruptcy prediction models utilize both statistical analysis and data mining technique to refine the decision support tools and improve decision making. The more recent data mining techniques include decision trees, neural networks (NNs), fuzzy logic, genetic algorithm (GA), support vector machine (SVM), generalized additive model (GAM) and so forth. Various researches have demonstrated that artificial intelligence (AI) techniques such as artificial neural network (ANN) can serve as a useful tool bankruptcy prediction. In the early stage of applying ANN to bankruptcy prediction, Back propagation neural network (BPNN) **Tam (1991) [6]** was used and their prediction results. Before that BPNN some of the technique followed such as recursive portioning, k- nearest neighbor, and tree algorithm ID3 but BPNN offered better predictive compare than compared models. Research efforts have been directed to integration of ANN models with other soft computing tools such as fuzzy sets **W.L. Tung(2004) [8]**, rough sets **B.J.Zaini(2008) [10]** and genetic algorithm (GA) **A.Tsakonas(2006) [9]**. Commonly used some other models today include Bayesian network **Arezoo (2009) [14]**, case based reasoning Li **& Sun (2009) [15]**, data envelopment analysis, ant colony optimization **Shuihua wang(2009) [7],** wavelet **Dong jing-rong (2009) [11],** ontology **Sotiris (2009) [36]**, particle swarm optimized **Li Rui (2010) [37] , [38] Hui li, Yee(2011)** Random subspace , **[39] Philippe (2009)** self organizing map and association rules.

In recent years there has been lot of interest in using kernels in various machine learning problems, with the SVM being the most prominent example. Traditionally SVMs, as well as other learning algorithm such as Neural Networks, are used for classification and pattern recognition applications. These learning algorithms have also been applied to general regression analysis: the estimation of function by fitting a curve to set of data points. The application of SVMs to general regression analysis case is called support vector regression (SVR). SVM and SVR are based on statistical learning theory or VC theory (VC- Vapnik, Chervonenkis), developed over the last decades.SVM first proposed by Vapnik was introduced in 1990s. SVM is implementing using the structural risk minimization principle which searches to minimize an upper bound of the generalization error. Thus, the solution for the SVM may be a global rather than a local optimum; SVM can minimize the risk of over fitting by choosing the maximum margin hyper plane in a feature space.

However, the SVM model suffers from imperfections while improving computational efficiency, optimizing model parameters, and selecting relevant input features. SVM model requires it to solve a quadratic programming problem, and, thus, is very slow when large scale practical problem. SVM modeling, some important parameters are needed to be optimized, which may affect the generalization performance of SVM. SVM model also encounters much difficulty some important features. The hybrid SVM learning approach model is designed to discover significant feature and to compute an accurate low dimensional embedding of high dimensional inputs.

2. SVM and HYBRID SVM

2.1 SVM

SVM Cristianini ,Hui Li (2000, 2011) [16,17] are considered a must try- it offers one of the most robust and accurate methods among all well-known machine learning algorithms. It has a sound theoretical foundation, requires only a dozen examples for training, and is insensitive to the number of dimensions. In addition, efficient methods for training SVM are also being developed at a fast pace.

In a two-class learning task, the aim of SVM is to find best classification function to distinguish between members of the two classes in training data. The metric of the concept of the "best" classification function can be realized geometrically. For a linearly separable dataset, a linear classification function corresponds to a separating hyperplane f(x) that passes through the middle of the two classes, separating of two. Once this function is determined, new data instance x_n can be classified by simply testing the sign of the function $f(x_n)$. x_n belongs to the positives class if $f(x_n)>0$.

Because there are many such a linear hyperplanes, what SVM additionally guarantee is that the best such a function is found by maximizing the margin between the two classes. Intuitively, the margin is defined as the amount of space, or separation between the two classes as defined by hyperline.. Geometrically, the margin corresponds to the shortest distance between the closest data points to a point on the hyperplane. Having this genetic definition allows us to explore how to maximize margin, so that even though there are an infinite number of hyperplanes, only a few quality as the solution of SVM.

The reason why SVM insists on finding the maximum margin hyperplanes is that is offers the best generalization ability. It allows not only the best classification performance on the training data, but also leaves much room for the correct classification of the future data.

2.2 Partial Least Squares (PLS) and SVM

The method combines the partial least squares **Zijiang yang (2011) [18]** based feature selection with Support vector machine for information fusion. PLS can identify complex nonlinearity and correlations among the financial indicators. It is the first time that PLS has been introduced into bankruptcy prediction. PLS is a supervised feature extraction method. By principal component analysis and the synthesis of variable extraction, the most comprehensive explanatory variables that predicted the variable Y were extracted PLS can separate the information and noise of the examined system so that the appropriate models can be established. The compression of information features based on the PLS compresses the explanatory variable X and also takes into account the correlation with the predicted variable Y. Its results will have more practical meanings.

PLS extracts the first latent variable t1 from the variable set X. t1 extracts as much variation information of X as possible. At the same time, it exacts the first latent variable u1 from the variable set Y to ensure the correlation between t1 and u1. Then the regression equations with Y and t1 and the equations with X and t1 are established. The algorithm terminates if the regression equation meets the accuracy requirements. Otherwise the second latent variable t2 was extracted from the residual information which has been interpreted by t1 of X, and u2 was extracted from the residual information which has been interpreted by t1 of Y. repeat this process until it reaches the required precision.

2.3 SVM Ensembles using Genetic Algorithm (GA)

Ensemble learning **Dae- ki kang (2010) [19]** is a method to improve the performance of classification and prediction algorithms. Ensemble learning performance degraded due to multicollinearity problem where multiple classifiers of an ensemble are highly correlated with. The method combines with the genetic algorithm to solve coverage optimization technique to guarantee the diversity of classifiers, enhance the stable performance enhancement of SVM ensembles and solve multicollinearity problem.

2.4 Fuzzy SVM

Fuzzy sets **Arindam (2011) [20]** are capable of handling uncertainty and impreciseness in corporate data. FSVM is effective in finding optimal features subset and parameters. A method for adapting it to default probability estimation is proposed. This work shows that FSVM are cable of extracting useful information from the financial data as compared to other approaches, although extensive data sets are required in order to fully utilize their classification power.

2.5 Hybrid manifold and SVM

The hybrid manifold learning **Fengyi (2011) [21]** approach model both isometric feature mapping (ISOMAP) algorithm and SVM. Manifold learning for dimensionality reduction is designed to discover significant feature and to compute an accurate low dimensional embedding of high dimensional inputs. ISOMAP algorithm for neighboring points the geodesic distances are approximated by the length of the shortest path in the graph with edge connecting nearby points. It applies classical scaling to the matrix of graph distances to obtain a representation of data in low dimensions.

2.6 SVM with Straightforward wrapper

SVM **[17]** is used to predict bankruptcy by utilizing a straightforward approach to help the model produce more accurate prediction. The wrapper approach fulfilled by employing forward feature selection method, composed of feature ranking and feature selection. Forward feature selection is an effective means to produce the optimal feature subset by progressively incorporating variables into larger and larger subsets. Using the process of feature ranking and forward selection can effectively help human beings pick out useful variables for the task of Bankruptcy prediction. Feature ranking is to find good variables and forward selection is to pick out good variables.

2.7 SVM and Support Vector Regression (SVR)

SVR **Mu-Yen (2010) [23]** is a revision version of SVM for regression. The model produced by support vector classification depends only on a subset of the training data, because the cost function of building the model does not care about training points that lie beyond the margin. Analogously, the model produced by SVR depends only on a subset of the training data, because the cost function for building the model ignores any training data close to the model prediction.

2.8 Hybrid Genetic algorithm (GA) and SVM

The methods propose GA **Sung-Hwan (2006) [24]** as the method of feature subset selection in the SVM system. This method uses the wrapper approach to select the optimal feature subset of the SVM model using GA. GA is used to optimize both the feature subset and parameters of SVM.

2.9 SVM with Optimal choice of kernel function parameters

Optimal parameter **jae.H.Min (2005) [25]** search plays a crucial role to build a prediction model with high prediction accuracy and stability; we employ a grid-search technique using 5-fold cross validation to find out the optimal parameters value of kernel function of SVM.

2.10 Real valued Genetic Algorithm (GA) to optimize parameters of SVM

Two parameters, C and σ, must be carefully predetermined in establishing an efficient SVM model. Therefore, the purpose of this concepts is to develop a genetic based SVM (GA-SVM) **Chih- Hung (2007) [30]** model that can automatically determines the optimal parameters of, C and σ, of SVM with the highest predictive accuracy and generalization ability simultaneously. The first parameter, C, determines the trade-offs between the minimization of the fitting error and the minimization of the model complexity. The second parameter, σ, it is the kernel function which defines the non-linear mapping from the input space to some high-dimensional feature space.

2.11 Neural Networks, Multivariate Statistical methods and SVM

This study aims to apply various neural network techniques, SVM and multivariate statistical methods **Melek acar (2009) [26]**. In the category of neural networks, four architecture namely multi-layer perception, competitive learning, self-organizing map and learning quantization are employed. The multivariate statistical methods; multivariate discriminant analysis, k-means cluster analysis and logistic regression analysis are tested.

A multi-layer perception is a feed-forward neural network with at least one or more hidden layer. The multi-layer networks involve the minimization of error function and they are trained by gradient descent method. Competitive learning has been mainly used for several input patterns. Self-organizing maps is feed forward neural network consisting of input and output layers of neurons. Linear quantization vector is an improved version of self-organizing map. Multivariate discriminant analysis is concerned with the classification of distinct sets of observations and it tries to find the combination of variables that predict the group to which an observation belongs. K-means cluster analysis which attempts to classify a set of observations into group like MDA. Logistic regression aims to correctly predict the group of outcome for individual observations using the most parsimonious model.

2.12 Hybrid approach of DEA, Rough set and SVM

In the proposed method **Ching-Chiang (2010) [27]** is employed as a tool to evaluate the input/output efficiency. Rough set theory, the redundant attribute in multi-attribute information table can be reduced, which showed that the number of independent variable was reduced with no information loss, is utilized as preprocessor to improve failure prediction capability by SVM. The result shows that DEA do provide valuable information in failure prediction.

2.13 Multiple Cases based reasoning (CBR) combined with SVM

CBR **Hui Li (2009) [28]** is an easily understandable methodology for problem solving. CBR is to meet new demands by revising old solutions, to explain new situations by using old cases, or to interpret new situations by reasoning from precedents. In this method, we develop a new combining classifiers system for failure prediction, where four independent CBR systems with k-nearest neighbor (KNN) algorithms are employed as classifiers to be combined, and SVM is utilized as the algorithm fulfilling combining classifier. The new combining classifiers system is named as multiple CBR systems by SVM. The four CBR systems, respectively, are found on similarity measure on the basis of Euclidean distance metric, Manhattan distance metric, grey coefficient metric, and outranking relation metric.

2.14 SVM +

In these concepts we focus on improving financial distress decision making by structuring information into heterogeneous groups of companies and by using advanced SVM+ **Bermardete (2010)[22]** technique. It is using privileged information regarding heterogeneous financial ratios grouped by the type of firms according to the number of employees and annual turnover of global balance. The approach takes a holistic view of the overall process enhancing the learning inductive process by improving generalization.

2.15 SVM with SFS and CART

The model integrates sequential forward selection (SFS), support vector machine (SVM), and classification and regression tree (CART). SFS, a typical heuristic searching scheme, identifies important features from unselected features and places them into a selected feature subset in each iteration. SFS is employed to overcome information overload problems. The PSO algorithm is an emerging population based meta heuristic that simulates social behavior, such as birds flocking to a promising position, to achieve precise objectives in a multi-dimensional space. To select the parameters of SVM models, particle swarm optimization (PSO) is applied. CART, a statistical procedure, is robust, easy-to-use decision tree tool that automatically shifts through large, complex databases in searching for and isolating significant patterns and relationships. CART is easy to grasp decision rules and reliable. The model can reduce unnecessary information and satisfactorily detect failures.

2.16 Nearest Neighbor SVM and correcting imbalanced samples

The model **Hui li (2011) [35]** investigates failure prediction based on the imbalanced data. The imbalanced dataset was collected and represented in terms of significant financial ratios, and new up-sampling approach and forecasting method were proposed to correct imbalanced samples. To balance the imbalanced dataset, the up-sampling method generates new minority samples according to random percentage distances from each minority samples according to its nearest neighbor (NN). The NNs of unbalanced samples are retrieved from the balanced dataset to produce a knowledge base of nearest -neighbor support vectors, from which base SVM are generated and assembled.

2.17 Bayesian and multiclass SVM

This method **Asma feki (2011) [34]** combines both gaussian bayes and different approaches of SVM. This classification problem involves many irrelevant variables and comparatively few training instances. New variable selection strategies are proposed. They are based on Gaussian marginal densities for Bayesian models and ranking scores derived from multiclass SVM.

2.18 Least squares SVM classifiers

LS-SVM **tony van gestel (2003) [29]** is a modified version of SVMs resulting into a set of linear equation instead of quadratic programming problems. LS-SVM classifier as computationally simple, but powerful nonlinear classifiers to predict failures. LS-SVM first map the data into higher dimensional feature space in which the discriminant function is constructed. The feature space formulation related to ridge regression, Fisher discriminant analysis and yields comparable classification performance.

2.19 Noisy-tolerant SVM

SVM **Zhong Gao (2008) [31]** are popular for popular for predicting failure. However, making inferences and choosing appropriate responses based on incomplete, uncertainty and noisy data is challenging in financial settings. In this method, proposed a new approach for enterprise failure prediction, which uses a novel SVM and k- nearest neighbor to remove noisy training examples.

2.20 SVM and sequential pattern mining

This method **Shan-chuan (2008) [33]** combines both SVM and binary sequential analysis (BSA). The BSA mines the predicting pattern from the SVM classification signals to predict next outcome of the company. BSA was used to extract prediction patterns from these sequential binary signals which were generated by the most accurate classification.

2.21 Manifold based semi- supervised discriminant analysis and SVM

This method **Shain –chang (2011) [32]** combines both manifold based semi supervised discriminant analysis (SSDA) and SVM. SSDA makes efficient use of labeled and unlabeled (testing) data points to gain perfect low dimensional approximation of data manifold and simultaneously maintain the discriminating power. SSDA outperforms other dimensionality reduction methods with a significant performance improvement.

Table 1. SVM and Hybrid SVM Characteristics

S. no	Method	Characteristics
1.	SVM	• SVM has only two free parameters, namely the upper bound and kernel parameter • SVM guarantee the existence of unique, optimal and global solutions. • Good generalization performance • Constructed with the small training data set size. • Structural risk minimization.

2.	Partial least square + SVM	Supervised feature selection
3.	Genetic algorithms + SVM ensemble	Solve optimization and solve multicollinearity problem
4.	Fuzzy + SVM	Handling uncertainty and impreciseness data and effective in finding optimal features
5.	Hybrid Manifold(ISO MAP+SVM)	Dimensionality reduction
6.	SVM+ straightforward wrapper	Feature ranking and feature selection
7.	SVM+ support vector regression	Revision version of SVM for regression
8.	Hybrid Genetic algorithm+ SVM	Feature subset selection and parameter optimization
9.	SVM + optimal of kernel function parameters	Find out the optimal parameter values of kernel function for predictive accuracy.
10.	Genetic algorithm + optimize parameter of SVM	Automated to determine the optimal values of SVM parameters for high predictive accuracy.
11.	Neural Networks, Multivariate Statistical methods + SVM	Multilayer perception and learning vector quantization – successful prediction models compare to competitive learning, self organizing map multivariate statistical methods.
12.	Hybrid approach of DEA, rough set +SVM	Better classification
13.	Multiple Case based reasoning(CBR) combined with SVM	Combining classifier system and it is feasible and validated
14.	(SVM+)	Support heterogeneous groups of companies
15.	SVM +SFS and CART	reduce unnecessary information and satisfactorily detect failures
16.	Nearest – neighbor+ SVM	Support for imbalanced datasets
17.	Bayesian + multiclass SVM	Improvement of prediction performance using only few variables.
18.	Least squares+ SVM classifiers	Better classification performance
19.	k-nearest neighbor+ SVM	Remove noisy data.
20.	SVM + sequential pattern mining	Correctness of SVM classification
21.	Manifold based semi-supervised discriminant analysis + SVM	Dimensionality reduction

3. CONCLUSION

This paper provides a survey of the previous work and state of the art in SVM for bankruptcy prediction with their associate applications references. SVM and hybrid SVM are powerful learning algorithms. SVM research continues to be a viable approach in the prediction of bankruptcy. Many methods and alternatives exist in the design of SVMs and great deal of flexibility is left to the designer in its implementation. Future studies will investigate new hybrid models of SVM.

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