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Abstract

Purpose – Credit risk assessment has gained importance in recent years due to global financial crisis and credit crunch. Financial institutions therefore seek the support of credit rating agencies to predict the ability of creditors to meet financial persuasions. The purpose of this paper is to construct neural network (NN) and fuzzy support vector machine (FSVM) classifiers to discriminate good creditors from bad ones and identify a best classifier for credit risk assessment.

Design/methodology/approach – This study uses artificial neural network, the most popular AI technique used in the field of financial applications for classification and prediction and the new machine learning classification algorithm, FSVM to differentiate good creditors from bad. As membership value on data points influence the classification problem, this paper presents the new FSVM model. The instances membership is computed using fuzzy c-means by evolving a new membership. The FSVM model is also tested on different kernels and compared and the classifier with highest classification accuracy for a kernel is identified.

Findings – The paper identifies a standard AI model by comparing the performances of the NN model and FSVM model for a credit risk data set. This work proves that that FSVM model performs better than back propagation-neural network.

Practical implications – The proposed model can be used by financial institutions to accurately assess the credit risk pattern of customers and make better decisions.

Originality/value – This paper has developed a new membership for data points and has proposed a new FCM-based FSVM model for more accurate predictions.

Keywords Membership, Generalization, Kernel, Back propagation-neural network (BP-NN), Classification accuracy, Fuzzy c-means (FCM), Fuzzy support vector machine (FSVM), Artificial intelligence (AI)

Paper type Research paper

1. Introduction

Credit risk analysis currently adopted by banks, insurance agencies, debt issuers and other financial institutions assess the creditworthiness of business or organizations. Most of the institutions deploy their own models to assess customer's potential based on risk, but this varies from product to product. Some use third party assistance like Standard and Poor's, Dun and Bradstreet, Fitch Ratings and Moody's for risk analysis. Since all firms cannot afford to take credit ratings from agencies, it has become necessary for financial institutions to use classification models in-house for discriminating good creditors from bad ones.

Michael B. Gordy (2000) performed a comparative study on the performance of two benchmark credit risk models, the Risk Metrics Group's Credit Metrics and Credit Suisse financial products Credit Risk$^+$. There is also considerable interest in identifying efficient models for classification and prediction of creditors trust-worthiness using statistical methods like multiple discriminant analysis (Pinches and Mingo, 1975), classification trees (Makowski, 1985), linear programming (Glover, 1990), KNN

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classifiers (Henley and Hand, 1996), etc. But, such models fail to address multivariate normality assumptions for independent variables in credit risk data sets. Huang *et al.* (2004) made a comparative study of credit rating analysis using back propagation-neural network (BP-NN) and support vector machine (SVM) and also interpreted the relative importance of financial variables using AI-based models. Recent research on credit risk analysis have focussed on using artificial intelligence tools like artificial neural network (ANN) (Lai *et al.*, 2006), SVM (Huang *et al.*, 2004), genetic algorithm (Chen and Huang, 2003), etc. Gang Wang and Jian Ma (2012) have described a hybrid ensemble approach for credit risk assessment based on RSB SVM. Maria Mavri (2013) proposed a framework for classifying Greek banks on bank rating index using hierarchical and k means clustering.

Most of the research papers in this field have focussed on model enhancement. We have developed a new computational procedure to prove model superiority over other FCM-based fuzzy support vector machine (FSVM) classifier models and have also compared it with other AI-based technique like neural network (NN) for credit risk analysis application.

ANNs, the most influential AI-based tool, has been used by researchers in financial time series applications (Sexton *et al.*, 1999). The most frequently used NN model is back propagation (BP) model due to its simplicity in architecture and its capability in learning complex data patterns. Surkan and Singleton (1990) applied BP-NN to classify the bonds of 18 Bell telephone companies and demonstrated that NN model achieved 88 percent accuracy in predicting direction of bond rating than multiple discriminant analysis technique. Kim *et al.* (1993) in a paper on bond rating prediction, justified the enhanced performance of NN model than linear regression, discriminant analysis, logistic regression and rule-based system. Since the NN model has over fitting issues, we have used another AI technique, the SVM, to develop a standard model for credit risk application.

The evolution of SVM, a new generation machine learning algorithm, has caused a paradigm shift in the field of machine learning and is being widely adopted by researchers working on classification and prediction problems. The concept emerged in 1995 at the conference on Computational Learning Theory by Vapnik and Cortes. SVM is based on the principle of structural risk minimization to avoid over fitting problems (Cortes and Vapnik, 1995). SVM, a supervised learning algorithm, constructs hyperplane to separate data points and classify them into predefined classes. The algorithm achieves maximum separation between the classes and minimum bound on the expected generalization error. The technique has therefore achieved maximum generalization performance in classification.

In situations when data points are not linearly separable by the classifier, non-linear mapping of data in higher dimensional space called "feature space" is done as a dot product and data are linearly separable by the hyperplane. To avoid explicit mapping of data points as dot products in higher dimensional space, kernel function $k(x_i, x_j)$ can be computed for training data set in input space, thereby enabling construction of SVM that operates in an infinite dimensional space (Soman *et al.*, 2009). SVM uses either quadratic programming or SMO or LS for construction of optimal hyperplane to classify the data points into respective classes. As SVM is affected by the presence of outliers or noise, fuzziness is incorporated into the SVM model. We use quadratic programming in solving non-linear FSVM classifier model.

Our paper is organized as follows: Section 2 describes AI-based tools – ANNs, advantage of using FSVM over SVM and membership generation for FSVM by proposed algorithm. Empirical analysis of BP-NN model and FCM-based FSVM model is discussed in Sections 3 and 4 concludes research findings.

2. Artificial intelligence techniques

2.1 ANN

In recent research studies, NNs have been used for predictive modeling in time seires forecasting (Tay and Cao, 2001), classification (Huang *et al.*, 2004) problems and default prediction (Kim and Sohn, 2010). ANN implements emprical risk minimization principle to minimize the generalization error (Tay and Cao, 2001), and the learning process enables ANN to solve non-linear, time variant problems under uncertain condition (Hussain, 2010). Researchers have tried different models such as Backpropagation, Kohonen, Hopfield and Radial Basis Function models (Engelbrecht, 2007). ANN is used as good analytical tool for pattern classification and prediction applications. In this study, we have constructed a BP-NN model consisting of an input layer, hidden layer and an output layer by considering the number of input variables as number of input nodes and prediction variable to be output node. In a work by Saravanan *et al.* (2010) the hidden neurons in ANN is varied from 2 to 30 and an optimal number is choosen based on accuracy. In a work by Kashman (2011), the number of hidden neurons is varied from 1 to 50 and the optimal number is choosen for a model that results in minimum time and cost. In our paper, the number of hidden neurons is calculated by (number of input nodes+number of output nodes)/2 (Huang *et al.*, 2004).

Although NN is generally successful, a few issues are associated with it, such as use of large controlling parameters, local minima leading to poor generalization performance and over fitting problem because of emprical risk minimization.

2.2 FSVM

SVM uses structural risk minimization principle to minimize upper bound of generalization error rather than minimizing training error like ANN. Though it is an effective classifier for binary classification, it is sensitive to outliers. To reduce the effect of outliers Lin and Wang (2002) proposed an extended model of SVM known as FSVM. The effect of outliers on classification accuracy is nullified by assigning membership values to each data point, as data points (fuzzy) defined as outliers or noise may not show exact belongingness to any of the defined classes. The data point detected as outlier is assigned low membership, to minimize its influence on error term and in the construction of decision plane. Hierarchical fuzzy speaker identification and brain MRI image segmentation based on FCM and FSVM have been proposed by earlier workers to select good training data and cluster (YuJuan *et al.*, 2012; Xiao and Tong, 2014). FSVM has shown better generalization than SVM in many real time applications like pattern classification (Inoue and Abe, 2001), credit risk evaluation (Wang *et al.*, 2005), text categorization (Wang and Chiang, 2007), ECG arrhythmia detection (Ozlem and Filkret, 2010), etc.

The FSVM procedure is described as follows:

A training set S is defined with associated membership values $(y_i, x_i, s_i), \ldots, (y_p, x_p, s_p)$, where each training data point $x_i \in R^n$ is given a class label $Yi \in \{1, -1\}$ and fuzzy membership values, where $0 < s_i \leqslant 1$ with $i = 1, \ldots, p$.

The optimal hyperplane classification problem (Lin and Wang, 2002) is given as:

$$\text{Minimize } \frac{1}{2} w^T w + c \sum_{i=1}^{p} s_i \varepsilon_i$$

subject to:

$$y_i(w.z_i + b) \geqslant 1 - \varepsilon_i \; i = 1, \ldots, p \tag{1}$$

and:

$$\varepsilon_i \geqslant 0, i = 1, \ldots, p$$

Here, c is a cost control parameter that controls the trade-off between maximization of margin and minimization of classifier error and the assignment of small value of s_i reduces the effect of error term ε_i on classifier performance, thereby rendering the corresponding data point less important.

Since the fuzzy membership s_i is the weight of the corresponding data point x_i toward one class and the parameter ε_i a measure of error in FSVM, the term $S_i\ \varepsilon_i$ a measure of error with different weights. The dual of the optimization problem is given as:

$$\text{Max } w(\alpha) = \sum_{i=1}^{p} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j Y_i Y_j K(x_i, x_j)$$

subject to:

$$\sum_{i=1}^{p} \alpha_i Y_i = 0 \tag{2}$$

$$0 \leqslant \alpha_i \leqslant s_i c i = 1, \ldots, p$$

On solving (2), $\alpha_i > 0$, is treated as the support vector. The data point x_i that falls on the hyperplane margin is said to be correctly classified, but taking the error term value of $0 \leqslant \varepsilon_i < 1$. The x_i located on the other side of the belongingness class is considered to be misclassified and takes the error term value $\varepsilon_i \geqslant 1$. The point x_i where $\alpha_i = 0$, is correctly classified and no error is observed (Soman *et al.*, 2009).

As the membership value of data points has considerable influence on the error terms, this paper focusses on developing a new membership function and incorporates a new membership value s_i into the FSVM model. This work also justifies classifier performance enhancement on credit risk data set.

2.2.1 Generation of membership. To minimize the effect of outliers by non-linear FSVM, the membership value for the data are an important input required in solving the quadratic programmng problem. Continuing work by Lin and Wang (2002), Wang and Chiang (2007) and Jiang *et al.* (2006), our work focusses on improving the generalization performance of classifier by proposing a new fuzzy membership for classification accuracy enhancment.

Xie and Beni (1991) first proposed fuzzy c-means (FCM) clustering algorithm, and the validity function for optimal number of clusters. Yang *et al.* (2011) had defined kernel FCM for generation of membership and took the values into FSVM model for classification problem. Wun *et al.* (2013) introduced a novel PIM fuzzy clustering algorithm to define robust fuzzy membership for FSVM. We have used FCM clustering algorithm to take fuzzy membership values for the FSVM model. The FCM algoritm used in generation of membership is as follows.

FCM minimizes the objective function with respect to fuzzy membership μ_{ij} and cluster cetroid V_i (Xie and Benni, 1991):

$$J_m = \sum_{i=1}^{c} \sum_{j=1}^{p} (\mu_{ij})^m d^2(X_j, V_i) \tag{3}$$

On solving (3), we obtain the membership values for the data set of each class as μ_1 and μ_2 from FCM algorithm, where μ_1 is the probability of data belonging to class 1 and μ_2 is the probability of data belonging to class 2. m is the fuzziness index. Each data holds two membership values. As data point belonging to one class is to be represented by one value of s_i for solving FSVM model, we define the membership by a fuzzy index m and compute the membership as:

$$S_i = \mathrm{abs}(\mu_1 - \mu_2)/m \tag{4}$$

where m is the fuzzy index.

Since error term is multiplied with membership value in the objective function (1), the data points detected as outliers with high-error term and membership will affect the classifier performance to greater extent. So, to reduce the effect of outliers on classifier performance, data points assigned with lower membership may significantly reduce its influence on error. Hence, by taking the difference of two membership values and also by introducing an index in the denominator (4), we can greatly reduce the membership values and influence of error terms in classification problem.

2.2.2 Proposed FSVM algorithm based on FCM algorithm. The FSVM algorithm based on FCM algorithm computational steps are as follows:

- Step 1: Initialize cluster parameters as number of clusters = 2, fuzzy index $m = 2$ and stopping criterion for validity function.
- Step 2: Observe the fuzzy membership values for data belonging to clustered groups from FCM.
- Step 3: Calculate the new fuzzy membership value for data using fuzzy index as $\mathbf{s_{i\,=}|\mu_{1-}\mu_2|m}$; where $m = 2$.
- Step 4: Train the non-linear FSVM classifier (say for RBF kernel) using new fuzzy membership values, cost control parameter c and kernel parameter γ.
- Step 5: Set the FSVM classifier model and predict the class label of the test data.
- Step 6: Validate the model by computing classifier accuracy.
- Step 7: Repeat the computational procedure for different values of c, and γ.
- Step 8: Terminate the process when the classifier model is tested for all combination of parameter values.
- Step 9: kernel parameter with c holding the highest accuracy rate is recorded.
- Step 10: Repeat steps 4 to 9 for another kernel function and terminate on testing with all functions.
- Step 11: Identify the best kernel with highest accuracy rate by comparative study.

3. Empirical analysis

In this section, we construct and evaluate performance of BP-NN model and FSVM classifier for credit risk data set (Beynon and Peel, 2001). The data set is on UK corporations from the financial analysis made easy CD-ROM database containing 30 failed and 30 non-failed firms described by 12 variables and decision variable by two classes as good creditors and bad creditors. The variables discussed are sales; profit before tax/capital employed (percent); funds flow (earnings before interest, tax and depreciation)/total liabilities; current liabilities long-term debt/total assets; current liabilities/total assets; current assets/current liabilities; current assets stock/current liabilities; current assets current liabilities/total assets; number of days between account year end and the date the annual report and accounts failed at company registry, number of years the company has been operating since incorporation date; CHAUD: coded 1 if auditor was changed in previous three years, else 0; BIG6: coded 1 if the company auditor is a BIG6 auditor, else 0.

3.1 ANN

The three layer BP-NN model is constructed using 12 input nodes, 6 and 7 hidden nodes and 1 output node. Instead of running the model for all possible hidden neurons as discussed in most of the papers, we calculated the hidden nodes to be 6.5 from calculation((input nodes + output node)/2), and the influence of hidden neurons on model performance is tested by running the model separately for 6 and 7 hidden nodes. The hidden nodes uses sigmoid transfer function. The model is tested using momentum coefficient value as 0.55 and number of epochs as 1,000 for the learning process. By varying the learning rate α and number of hidden neurons for 6 and 7, the model performance for low MSE is tested. We use MATLAB 7.9.0.529 NN toolbox for implementation of BP-NN model. Table I shows the BP-NN model performance.

The model analysis results shows that for hidden neurons 6 and learning rate 0.04, the BP model performs best at 77.62 percent with MSE of 0.2238. The model with this control parameters setting is considered the standard BP-NN model for credit risk application.

3.2 FSVM classifier

As kernels influence classifier performance under non-linear condition, RBF, polynomial, and MLP kernel function is used in FSVM model and the classifier performance is compared for computation of new membership values.

In our experiment, we use the FCM-based FSVM algorithm to perform classification on the credit risk data set. The experiments are done as follows: we run FCM algorithm to determine the membership of the data for fuzzy index $m = 2$ and compute new membership values as described in membership generation. Next, we use fivefold cross-validation, where data sets are divided into five equal subsets keeping one subset as test set and remaining four sets as training sets. Then, we test the FSVM model using cost control parameter $c = \{2^9, 2^7, 2^5, 2^3, 2^1, 2^{-1}, 2^{-3}, 2^{-5}, 2^{-7}, 2^{-9}\}$ on RBF kernel parameter $\gamma = \{2^{-9}, 2^{-7}, 2^5, 2^{-3}, 2^{-1}, 2^1, 2^3, 2^5, 2^7, 2^9\}$; polynomial kernel parameter $d = \{2, 3, 4, 5\}$ and MLP kernel parameter $p = \{(-1, 1), (-0.7, 0.7), (-0.5, 0.5), \text{and so on}\}$ and run the algorithm to test the performance of classifier accuracy. The accuracy is calculated by adding correctly classified data in both classes and dividing by the total number of data points. This observation is made from a confusion matrix created in the algorithm. In the computational process, we observe the classification accuracy rate for the kernel and c parameter. The method uses grid search (Ogut *et al.*, 2009) to assess the best parameter values that show highest rate of accuracy. The kernel parameter with c

Table I. BP-NN model performance on credit risk data set

Hidden neurons	Learning rate α	Accuracy (%)	MSE
6	0.05	71.26	0.2874
	0.04	77.62	0.2238
	0.03	57.58	0.4242
7	0.06	57.61	0.4239
	0.05	71.20	0.2880
	0.04	49.67	0.5033

having the highest accuracy is identified as the best parameter value that can fit the model. Table II shows the computational results of credit risk data set using grid search for RBF kernel function.

It can be seen from the table that for $c = 2^9$ and $\gamma = 2^7$, FSVM model performs well with the highest accuracy rate of 78.83 percent. So, this can be chosen as the best parameters that could fit the model. To test the influence of other kernel functions, the model is run using other kernels using same computational procedure and from the comparative study, the kernel with the highest classification accuracy is chosen as the best kernel for the FSVM model. We use MATLAB 7.9.0.529 SVM toolbox for implementation of FSVM model and for the computational process.

The comparative statement of computational results and illustration for different kernel functions are listed in Table III.

It is seen from the computational performance of credit risk model that polynomial kernel function enhances classifier accuracy by 80 percent for the best combination of parameters $c = 2^9$ and $d = 2$ than RBF and (MLP) sigmoid kernels. The proposed model performs better than the model presented by Wang *et al.* (2005). Although Wang *et al.* have shown classifier enhancement using bilateral FSVM with the maximum accuracy of 79 percent as compared to unilateral FSVM by defining membership functions, our model has outperformed the said model with an accuracy of 80 percent.

4. Conclusion

In this paper, we have developed a BP-NN model to assess credit risk of customers by financial institutions and have also proposed a FCM-based FSVM incorporating new fuzzy membership using kernel functions like RBF kernel, polynomial, and MLP for the application. The effect of outliers on classifier performance could be reduced by setting low-membership values for data point acting as outliers. Thus, the new membership formulated reduced the membership values and the effect of outliers on model. The experimental results of two models have shown that the proposed method of

C/γ	2^{-5}	2^{-3}	2^{-1}	2^1	2^3	2^5	2^7	2^9
2^9	50	50	51.67	68.45	70	71.667	78.83	75
2^7	50	51.67	51.67	53.33	70	78.33	76.67	53.33
2^5	50	51.67	51.67	53.33	68.33	75	75	50
2^3	50	51.67	51.67	53.33	73.33	76.67	55.5	50
2^1	50	51.67	53.33	53.33	53.33	53.33	53.33	53.33
2^{-1}	50	50	50	50	50	50	50	50
2^{-3}	50	50	50	50	50	50	50	50
2^{-5}	50	50	50	50	50	50	50	50

Table II. FSVM model performance for RBF kernel function

			Kernel function output	
Kernel	c	Kernel parameter	Accuracy (%)	Error rate (%)
RBF	2^9	$\gamma = 2^7$	78.33	21.67
Polynomial	2^9	d = 2	80	20
MLP	2^1	$p = (0.5, -0.5)$	75	25

Table III. Comparative analysis of FSVM model on different kernel functions

FSVM classifier enhanced the performance with classifier accuracy rate of 80 percent as compared to BP-NN model with a classifier accuracy rate of 77.62 percent.

A model that misclassifies an important customer as default can be catastrophic to the organization. Thus, it is important for financial organizations to develop a standard model with minimum misclassification and maximum classification accuracy. Our proposed model of FSVM for credit risk analysis will be of immense use to financial institutions for discriminating customers due to its good classification accuracy.

Glossary

AI	artificial intelligence
ANN	artificial neural network
SVM	support vector machine
FSVM	fuzzy support vector machine
FCM	fuzzy c-means
BP-NN	back propagation-neural network
RBF	radial basis function
MLP	multi layer perceptron
MSE	mean square error

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