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Usefulness of support vector machine to develop an early warning system for financial crisis

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ABSTRACT

Oh, Kim, and Kim (2006a), Oh, Kim, Kim, and Lee (2006b) proposed a classification approach for building an early warning system (EWS) against potential financial crises. This EWS classification approach has been developed mainly for monitoring daily financial market against its abnormal movement and is based on the newly-developed crisis hypothesis that financial crisis is often self-fulfilling because of herding behavior of the investors. This article extends the EWS classification approach to the traditional-type crisis, i.e., the financial crisis is an outcome of the long-term deterioration of the economic fundamentals. It is shown that support vector machine (SVM) is an efficient classifier in such case.

1. Introduction

Recently the financial crises have been sweeping across the major economies and threatened the stability of the international monetary market. To be prepared against such crises, it is quite necessary to have proper early warning system (EWS) that alarms against possible financial crises. In fact, numerous theoretical and empirical works have been done to investigate the economic or financial crisis and build EWS (Goldstein, 1996; Kaminsky & Reinhart, 1999; Khalid & Kawai, 2003). It is a well-accepted view that there are two kinds of explanations regarding financial crises. A classical explanation is that financial crisis is an outcome of long-term deterioration of economic fundamentals. A recent view, however, asserts that financial crisis is self-fulfilling in the sense that crisis occurs by change of expectations of market participants, not entirely by fundamental change of market conditions (see, e.g., Obstefeld, 1986). Indeed, the recent view asserts that stock market crash or frenzied selling mainly driven by irrational herding behavior could lead to a major financial crisis. A typical example of this phenomenon is the financial crisis that many Asian nations had experienced in 1997. Against this type of crisis, it is essential to prepare EWS monitoring market movement on a *daily* basis and Oh, Kim, and Kim (2006a), Oh, Kim, Kim, and Lee (2006b) successfully developed such a system via classification approach, say DFCI (daily financial market condition indicator). Roughly speaking, their EWS (or EWS classification approach) monitors and classifies the financial market on the basis of daily financial market movement. In order to achieve desirable accuracy of their EWS, it is important to find an efficient classifier and Kim, Hwang, and Lee (2004), Kim, Oh, Sohn, and Hwang (2004) actually found that neural network (NN) may monitor daily financial market effectively and Oh and Kim (2007) showed that an improvement over NN is possible by case-based reasoning (CBR).

In this article we extend the EWS classification approach to produce EWS for the traditional-type crisis. Recall that this definition of crisis focuses on long-term and continuous deterioration of economic fundamentals as the major source of trouble. Since there are quite a number of such economic fundamental variables, it is occasionally the main concern of the traditional-type crisis to find "a proper subset of the variables" that describes the crisis efficiently. For instance, Kaminsky, Lizondo, and Reinhart (1998) proposed to use a signal to noise ratio to select a proper subset of given crisis-related variables. This selection procedure might be technically necessary in view of sparsity of data which is originated from the sparsity of crisis itself. In other words, the selection procedure usually comes to support the technically desirable condition that the dimension of data is to be less than the size of data. In this article, our EWS (based on the EWS classification approach) considers all given crisis-related variables available instead of finding a small subset of them and then builds *monthly financial market condition indicator* (MFCI). Note that DFCI uses *daily* financial market data that are plentiful in their character and hence rarely suffers from sparsity of data.

There are two major findings in this article. The first finding is that support vector machine (SVM) is an appropriate EWS classifier for the traditional-type crisis. The second finding is that MFCI based on monthly economic variables behaves similarly to DFCI

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based on daily financial market movements. The latter is interesting from economic point of view since MFCI does not utilize the daily financial market movement used for DFCI but behaves similarly as DFCI. These will be verified empirically by applying the EWS classification to building MFCI for the Korean economy. In addition, it is technically worth mentioning that we introduce a new transformation of crisis-related variables to detect traditional-type crisis more effectively. In fact, the "run" of the crisis-related variable is included as a monitoring variable against continuous deterioration of the economic fundamentals. See, e.g., X2, X9, X13, X14, X17 and X18 of Table 2. The rest of the study consists of as follows: Section 2 discusses the EWS classification approach and SVM. In Section 3, we construct MFCI for the Korean financial market via SVM and compare it with other classifiers. Lastly, the concluding remarks are given in Section 4.

2. Technical issues

2.1. Support vector machine

SVM is a learning machine that can perform pattern recognition tasks based on the statistical learning theory presented by Vapnik (1998). The basic concept of SVM considers a typical two-class classification problem (see Kecman, 2001; Schölkopf and Smola, 2000; Cristianini and Shawe-Taylor, 2000). SVM is known as the algorithm that finds a special kind of linear model, the maximum margin hyperplane. Consider the problem of separating the set of training vector belonging to two separate classes, $G = \{(xi, y_i), i = 1, 2, \dots, N\}$ with a hyperplane $\mathbf{w}T\mathbf{x} + b = 0$ ($\mathbf{w} \in R^d$ is a normal vector, $\mathbf{x}_i \in R^d$ is the ith input vector and $y_i \in \{-1, 1\}$ is a known binary target). The original SVM classifier satisfies the following conditions:

$$y_i(\mathbf{w}^T\mathbf{x}_i + b) \geqslant 1, \quad i = 1, 2, \dots, N. \tag{1}$$

The maximum distance between two hyperplanes, $\mathbf{w}^T\mathbf{x}_i + b = 1$ and $\mathbf{w}^T\mathbf{x}_i + b = -1$, is $2/\|\mathbf{w}\|$. Hence, we can find the optimal hyperplane by solving the optimization problem:

$$\min_{b,\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 \tag{2}$$

under the constraints of Eq. (1). The solution to the above problem is equivalent to determining the saddle point of the Lagrange function, i.e.,

$$\min_{\mathbf{w},b} L = \min_{\mathbf{w},b} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{N} \alpha_i [y_i(\mathbf{w}^T\mathbf{x}_i + b) - 1] \right\} \tag{3}$$

subject to $\alpha_i \geqslant 0$ for $i = 1, 2, \dots, N$. At the optimal point, we have the following saddle point equations:

$$\frac{\partial L}{\partial \mathbf{w}} = 0 \quad \text{and} \quad \frac{\partial L}{\partial b} = 0 \tag{4}$$

which implies

$$\mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i \quad \text{and} \quad \sum_{i=1}^{N} \alpha_i y_i = 0. \tag{5}$$

Substituting Eq. (5) into Eq. (3), we obtain the dual quadratic optimization:

$$\max L_D = \max \left[\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j \right] \tag{6}$$

subject to $\sum_{i=1}^{N} \alpha_i y_i = 0$ and $\alpha_i \geqslant 0$ for $i = 1, \dots, N$. The Karush–Kuhn–Tucker (KKT) optimality conditions play an important role in determining the optimal value of the b and $\mathbf{w}$, respectively, i.e.,

$$b = y_i - \mathbf{w}^T\mathbf{x}_i \quad \text{for } i = 1, \dots, N, \tag{7}$$

$$\mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i. \tag{8}$$

Note that the classification task is only a function of the support vectors, the training data that lie on the margin.

For a non-separable case, we introduce a slack variables ξ_i and penalty C to formulate soft margin as follows:

$$\min \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N} \xi_i \tag{9}$$

subject to $y_i(\mathbf{w}^T\mathbf{x}_i + b) \geqslant 1 - \xi_i$, $i = 1, 2, \dots, N$ and $\xi_i \geqslant 0$ for all i. By applying the Lagrangian technique to Eq. (9), we will have a similar dual quadratic optimization problem like Eq. (6),

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j \tag{10}$$

subject to

$$\sum_{i=1}^{N} \alpha_i y_i = 0, \quad 0 \leqslant \alpha_i \leqslant C, \; i = 1, \dots, N. \tag{11}$$

Since real-life pattern recognition problems cannot be solved using linear machine learning algorithms, a non-linear decision function must be applied. Hence, the linear classification problem must be converted into a non-linear classification problem by the mapping function Φ. By applying the kernel function $(\Phi^T(\mathbf{x}_i), \Phi(\mathbf{x}_j)) = K(\mathbf{x}_i, \mathbf{x}_j)$ to Eq. (11), we will obtain a following equation:

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{12}$$

subject to Eq. (11). Followed by the steps described in the liner generalized case, we obtain decision function of the following form:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \sum_{j}^{N} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}_j) + b \right). \tag{13}$$

Any function satisfying the Mercer's condition (Vapnik, 1995) can be used as the kernel function. There are different kernel functions used in SVM, such as linear, polynomial, and radial basis function (RBF). In this study, RBF kernel $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2)$ is used as a kernel function of SVM since the RBF kernel tends to give good performance under general smoothness assumptions. Note that SVM has reported excellent performances in financial applications. For instance, time series prediction such as stock price index (Cao & Tay, 2001; Tay & Cao, 2002), classification such as credit rating (Huang, Chen, Hsu, Chen, & Wu, 2004), and bankruptcy prediction (Fan & Palaniswami, 2000) are the main applicable areas of SVM.

2.2. EWS classification approach

Kim, Hwang, et al. (2004), Kim, Oh, et al. (2004) first proposed the classification approach for establishing EWS for the economic crisis and Oh et al. (2006a, 2006b) has used it to develop *daily* financial condition indicator (DFCI). DFCI proved to register a good performance in judging the given financial market condition in the sense that it reflects the real financial market situation fairly accurately. In the EWS classification approach, the financial market conditions are classified into three phases: (i) stable period (SP), (ii) unstable period (UP), and (iii) crisis period. It is UP that gives the unique feature to the classification approach, i.e., the EWS based on the classification approach is designed to activate (or issue a warning) whenever the financial market enters the UP. As the UP usually occurs just prior to a crisis, it can be interpreted as a

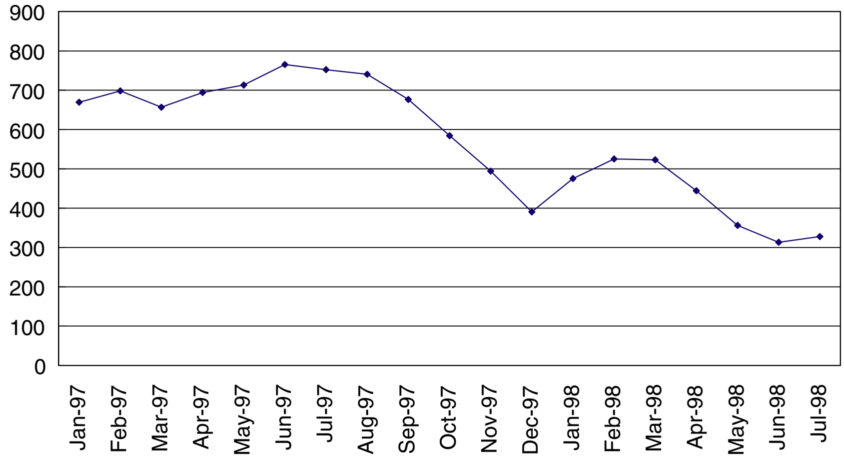

Fig. 1. KOSPI of training period (from January 1997 to July 1998).

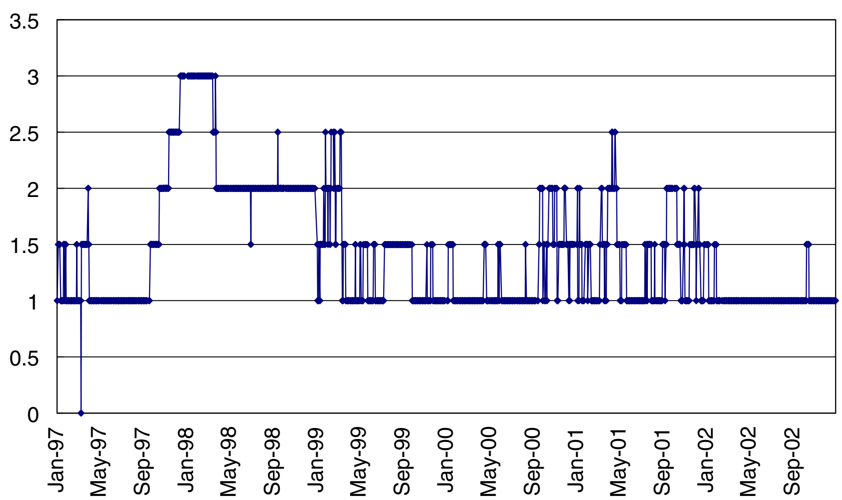

Fig. 2. DFCI from January 1997 to December 2002 developed by Oh et al., 2006a, 2006b.

Table 1
Specific dates of SP, UP and CP for training data.

Phase	Period
SP (1)	January, 1997–July, 1997
UP (2)	August, 1997–January, 1998
CP (3)	February, 1998–July, 1998

phase through which the financial market makes a transition from SP to CP. Often it is called a gray zone where the self-correcting mechanism of the financial market deteriorates and it is characterized by a sudden change of volatility level and rapid swings in the market sentiments. Note that the financial market in the UP may either proceed to a crisis or return to a stable condition.

For a more concrete description of the EWS classification approach, suppose that we have a historical period $T_{\alpha,\beta} = \{t : t_\alpha \leqslant t \leqslant t_\beta, \alpha \leqslant \beta\}$ which contains economic or financial crisis having occurred in the past. Furthermore, assume that the economic or financial condition of those periods are classified into three categories or phases; (i) stable period (SP or $y = 1$), (ii) unstable period (UP or $y = 2$), and (iii) crisis period (CP or $y = 3$). In other words,

$$\Delta_{\alpha,\beta} = \{(T_1, T_2, T_3) : T_{\alpha,\beta} = \cup_{i=1}^{3} T_i,\ T_i \cap T_j = \phi,\ i \neq j\}, \tag{14}$$

where T_p denotes a subset of $T_{\alpha,\beta}$ such that economic condition is $y = p$ on T_p. Now from decomposition $\Delta_{\alpha,\beta}$, one may establish training data set. Suppose that we have input vector $\mathbf{x}_i = (x_{i1}, \ldots, x_{id}) \in R^d$ where x's are economic or financial variables related to crisis. Then

$$\mathbf{T}_N(\alpha, \beta) = \{(\mathbf{x}_i, y_i) : i = 1, \ldots, N\} \tag{15}$$

forms a desired training data set of sample size N, which produces a regular classifier $\hat{f} : R^d \to \{1, 2, 3\}$. Here $y_i = p$ whenever $i \in T_p$ for $p = 1, 2, 3$ and note that it possible to have $d > N$.

3. Case study: MFCI for the Korean financial market

Korea had experienced a major financial market crisis during 1997–1998 that started as a currency crisis caused by bank liquidity. In this section MFCI against the traditional-type crisis is established for the Korean financial market by the EWS classification approach. It is shown that MFCI performs reasonably well and SVM is an appropriate classifier for such MFCI, compared to other classifiers.

Table 2
The list of input variables.

	Selected variable	Explanation
X1	Note default rate (NDR)	Using raw data
X2	Size of the run of increasing X1 during the latest 12 months	$\sum_{i=t-11}^{t}(Z1)_i, Z1 = 1$ if $(X1)_t > (X1)_{t-1}$; 0, otherwise
X3	Change rate of foreign exchange holdings (FEH)	Ratio of the current month to the same month of the last year
X4	Change rate of money stock	Ratio of the current month to the same month of the last year
X5	Change rate of producer price index	Ratio of the current month to the same month of the last year
X6	Change rate of consumer price index	Ratio of the current month to the same month of the last year
X7	Change rate of balance of trade	Ratio of the current month to the same month of the last year
X8	Change rate of index of industrial production	Ratio of the current month to the same month of the last year
X9	Size of the run of decreasing X8 during the latest 12 months	$\sum_{i=t-11}^{t}(Z8)_i, Z8 = 1$ if $(X8)_t < (X8)_{t-1}$; 0, otherwise
X10	Change rate of index of producer shipment	Ratio of the current month to the same month of the last year
X11	Change rate of index of equipment investment	Ratio of the current month to the same month of the last year
X12	FEH per gross domestic products	FEH/GDP
X13	Size of the run of decreasing X12 during the latest 12 months	$\sum_{i=t-11}^{t}(Z8)_i, Z12 = 1$; if; 0, otherwise
X14	Size of the run of decreasing monthly change of X12 during the latest 12 months	$\sum_{i=t-11}^{t}(Z12)_i, Z12 = 1$ *if* $(X12)_t < (X12)_{t-1}$; 0, otherwise
X15	Change rate of FEH per GDP	Ratio of the current month to the same month of the last year
X16	Balance of trade per GDP	BOT/GDP
X17	Size of the run of increasing X16 during the latest 16 months	$\sum_{i=t-11}^{t}(Z16)_i, Z16 = 1$ if $(X16)_t < (X16)_{t-1}$; 0, otherwise
X18	Size of the run of negative X16 during the latest 16 months	$\sum_{i=t-11}^{t}(Z16)_i, Z16 = 1$ if $(X16)_t < 0$; 0, otherwise
X19	Difference between loan and deposit rates	Using raw data
X20	Trade terms	Using raw data
X21	Difference between domestic and foreign interest rates	Using raw data
X22	Portfolio investments	Using raw data

Table 3
Training results of five classifiers.

Classifier	Hit ratio (%)
SVM	100
MLR	89.47
DT	100
CBR	94.74
NN	100

3.1. Training dataset

Let $\{(\mathbf{x}_i, y_i):\mathbf{x}_i \in R^d, y_i = 1, 2, 3, i = T_0, \ldots, T_0 + N - 1\}$ be the training data set. Here $\mathbf{x}$, y, N and T_0, respectively, denote d-dimensional input vector, response (i.e., 1, 2 and 3 mean SP, UP and CP), the size of training data and the starting time point. For starting the EWS classification approach, the training period (or training data) is first established as the period from January 1997 to July 1998 (i.e., $N = 19$) which includes November 1998, the month when the Korean economy was officially declared by IMF (International Monetary Fund) to have entered into the major crisis. For reference, the monthly KOSPI (Korea Stock Price Index) during that period is given in Fig. 1. To complete the training data construction, the values of y's ($y_{T_0}, \ldots, y_{T_0+18}$ with T_0 being January 1997) are specified as one of 1, 2, 3 by referring to the classification results of DFCI given in Fig. 2 (also refer to Kim, Oh, et al. (2004) and Oh et al. (2006a, 2006b)). See Table 1.

For input variables, a set of the well-known traditional crisis-related variables are considered on the basis of how well they supply the information about the economic fundamentals (see, e.g., Kaminsky and Reinhart, 1999; Goldstein, 1996; Oh et al., 2006a, 2006b or Khalid and Kawai, 2003). As mentioned previously, some transformations of the original variables based on the "run" are introduced to measure the "continuous" deterioration of the economic fundamentals which is a theoretically essential part of the traditional-type crisis. See Table 2. Thus 22 input variables are

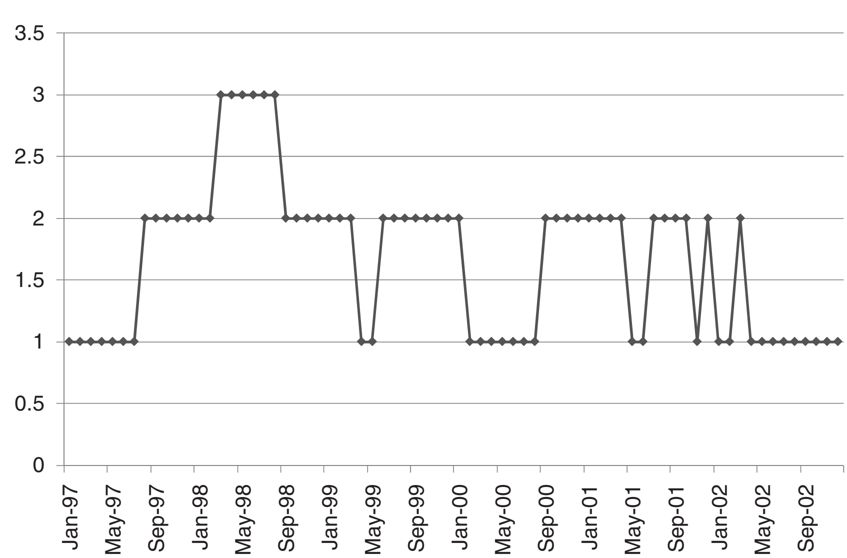

Fig. 3. Classification result of the MFCI using SVM from January 1997 to December 2002.

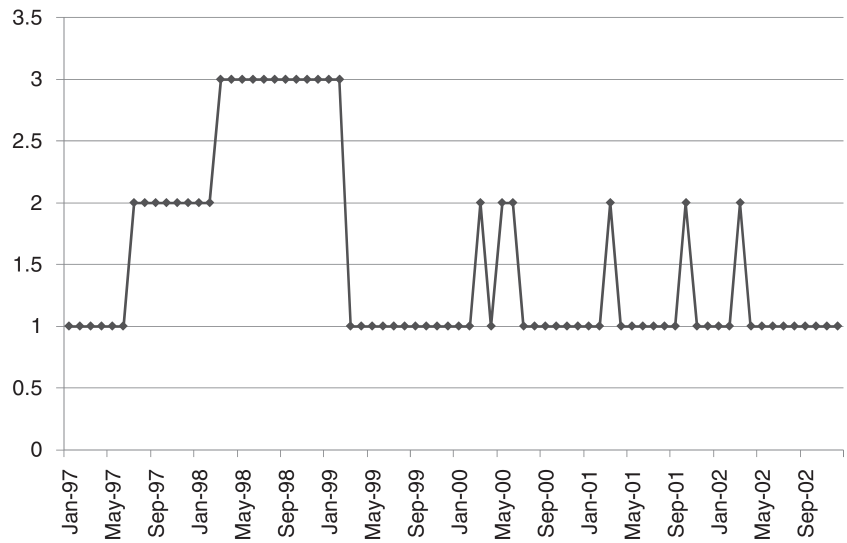

Fig. 4. Classification result of the MFCI from January 1997 to December 2002.

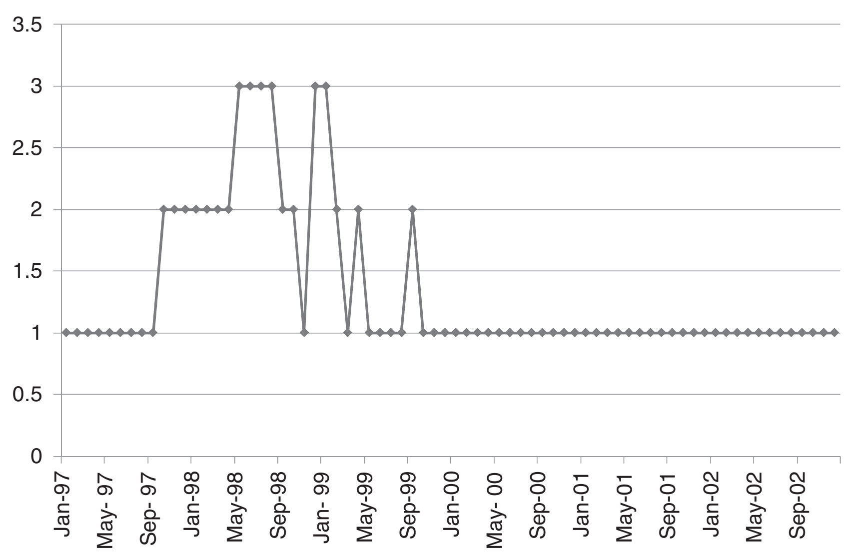

Fig. 5. Classification result of the MFCI using MLR from January 1997 to December 2002.

obtained with $\mathbf{x} = (x_1, \ldots, x_d) \in R^d$ and $d = 22$. Note here that all 22 variables are monthly data and $d = 22 > N = 19$.

3.2. SVM for EWS classification

SVM is considered for establishing MFCI. To demonstrate the appropriateness of SVM for MFCI, four other classifiers are considered for comparison, i.e., MLR (multivariate logistic regression), DT (decision tree), CBR (case-based reasoning), and NN (neural network). In order to treat the EWS classification approach in the context of forecasting, we employ lag l(=1) classifier recently proposed by Son, Oh, Kim, Won, and Do (2009) as a modified version of the regular EWS classifier. Consider lag-1 forecasting or classification model defined as

$$y_{t+1} = f_1(x_{t1}, \ldots, x_{td}), \tag{16}$$

where f_1 is a lag-1 classifier with a set of input variables $(x_{1t}, \ldots, x_{dt})$ and the discrete (or categorical) response variable y_{t+1}. For model (18), the training data set of size $N = 19$ is given by

$$\Xi_N = \{(x_{1,T_0-1}, \ldots, x_{d,T_0-1}, y_{T_0}), \ldots, (x_{1,T_0+N-2}, \ldots, x_{d,T_0+N-2}, y_{T_0+N-1})\}. \tag{17}$$

Then Ξ_N produces lag-1 classifier or forecaster

$$\hat{f}_1 : \mathbf{X} \to \mathrm{Y} \tag{18}$$

which maps $\{x_t = (x_{1t}, \cdots, x_{dt}){:}t = T_0 - 1, \ldots, T_0 + 17\}$ to its classification label $\{(y_{T_0}, \ldots, y_{T_0+18})\}$. Training results of the five classifiers are given in terms of hit ratio in Table 3, which indicates their fairly good training results.

For implementing SVM in establishing MFCI, RBF kernel is employed as the kernel function since the RBF kernel tends to give

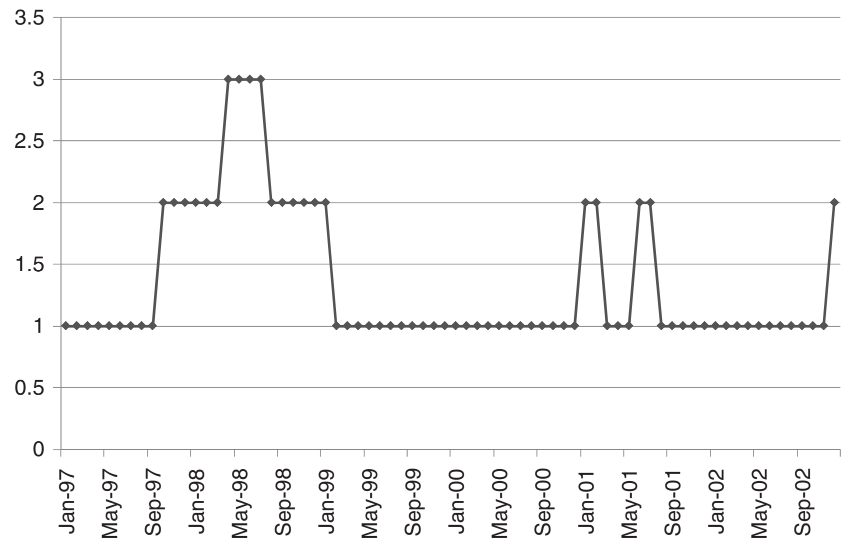

Fig. 6. Classification result of the MFCI using CBR from January 1997 to December 2002.

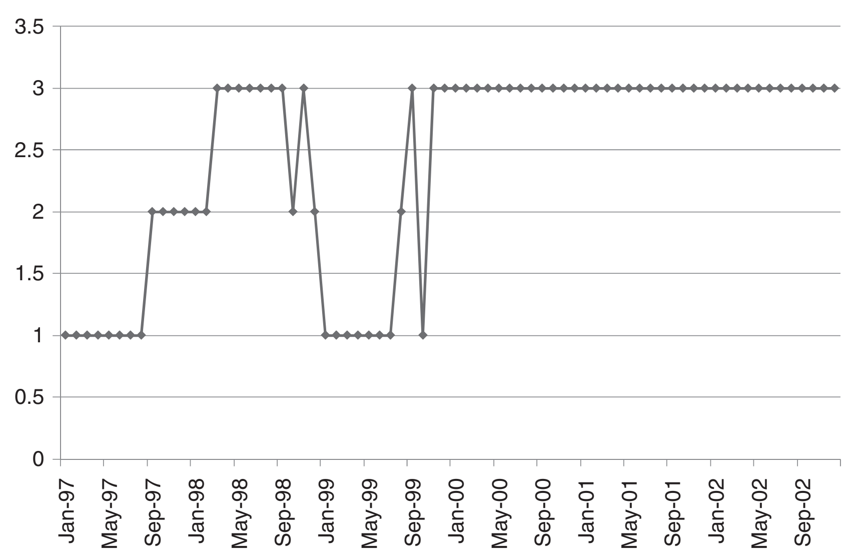

Fig. 7. Classification result of the MFCI using NN from January 1997 to December 2002.

reasonably good performance under general smoothness assumptions. When the RBF kernel is selected, only two parameters, C and σ, are needed and in this experiment the values of C and σ are set to be 100 and 2, respectively. Fig. 3 shows MFCI established by SVM. Testing period is from January 1997 to December 2002 minus the training period. One may notice that, roughly, DFCI (Fig. 2) and MFCI (Fig. 3) show similar movements. This is interesting since MFCI does not use the information on daily financial market movements that DFCI is critically based on. Recall that the DFCI is known to perform reasonably well for the Korean economy in the sense that it corresponds well to the past events that have occurred in the Korean economy (Oh et al., 2006a, 2006b).

For studying an appropriate classifier for MFCI, other classifiers are considered. Indeed DT (decision tree), MLR (multivariate linear regression), CBR (case-based reasoning) and NN (neural network) are employed for MFCI construction in Figs. 4–7, respectively. Note that some parameter adjustments are made for efficient implement of each classifier and their training results are given in Table 3. From Figs. 2–7, one may easily notice that SVM in Fig. 3 is closer to DFCI in Fig. 2 than the others. One possible explanation for this might be obtained from Hall, Marron, and Neeman (2005) which proves SVM as an efficient tool particularly for classification problem with $d > N$. On the other hand, it also shows that other classifiers (DT, MLR, CBR and NN) might fail to function for $d > N$ in the sense that they behave quite differently from the DFCI given in Fig. 2. Recall that NN and CBR (not SVM) work better than the others for DFCI. For reference, Table 4 is given to demonstrate that MFCI matches the events having occurred to the Korean economy.

Table 4
Monthly chronicle of Korean economy (1997.1–2002.12).

Year	Month	Description of major events	Value of MFCI (or SVM)
1997	01[a]	Bankruptcy of Hanbo Group	1
	02[a]		1
	03[a]	Bankruptcy of Sammi Group	1
	04[a]	Liquidity crisis of Jinro Group	1
	05[a]	Liquidity crisis of Daenong and Kia Motors	1
	06[a]		1
	07[a]		1
	08[a]		2
	09[a]		2
	10[a]	Bankruptcy of Kia Motors	2
	11[a]	Bankruptcy of Haitai Group and New Core Group	2
	12[a]	Bankruptcy of Halla Group	2
1998	01[a]	Bankruptcy of Nasan Group and Keukdong Construction Co.	2
	02[a]		3
	03[a]	Bankruptcy of Jeil Financial Co.	3
	04[a]		3
	05[a]	Bankruptcy of Donga Construction Co.	3
	06[a]		3
	07[a]	Major banks enter into workout	3
	08	Bankruptcy of major Insurance Companies	3
	09	Bankruptcy of Kukje Company	3
	10	Bankruptcy of Kapul Group	3
	11		3
	12		3
1999	01		1
	02		3
	03	Unemployment rates reached 9%	3
	04	Bankruptcy of Daehan Finance Co. and nine minor banks	1
	05		1
	06	Bankruptcy of Samsung Motors	1
	07	Liquidity crisis of Daewoo Group	2
	08	Liquidity crisis of Daewoo Group	2
	09	Liquidity crisis of Daewoo Group	2
	10		1
	11	Six companies of Daewoo Group enter into workout	1
	12		1
2000	01		1
	02		1
	03		2
	04	Liquidity crisis of Hankuk and Daehan Trust & Investment Co.	2
	05	Saehan Group enters into workout	1
	06	Liquidity crisis of Hyundai Group	2
	07	Business suspension of three minor banks	1
	08	Bankruptcy of Woobang Co. and Hankuk Financial Co.	1
	09	Liquidity crisis of Daewoo Motors	3
	10	Liquidity crisis of Donga Constructions Co.	1
	11	Liquidity crisis of Hyundai Construction Co.	3
	12	Default rates increase suddenly	3
2001	01		3
	02	Bankruptcy of Hankuk Real Estate Trust Co.	3
	03	Bankruptcy of Korea Industrial Development Co.	3
	04	Liquidity crisis of Hyundai Construction Co.	3
	05		3
	06		3
	07	Business Suspension for 18 major companies	3
	08		3
	09	9/11 terror for World Trade Tower in NY	1
	10		3
	11		1
	12		1
2002	01		1
	02		1
	03		1
	04		1
	05		1
	06		1
	07		1
	08		1
	09		1
	10		1
	11		1
	12		1

[a] Training period (1997.1–1998.7) is decomposed into three periods (SP, TP, CP).

4. Concluding remarks

Recent financial crises in many parts of the world have rekindled the research for constructing EWS that had been sparked and started by the 1990s economic crises. In this article, EWS (or MFCI) is constructed for the traditional-type economic crisis by formulating it into a classification problem. Our studies show that SVM is an appropriate tool for MFCI and that MFCI behaves similarly to DFCI. The fact that SVM is an appropriate tool for MFCI empirically verifies SVM to be an efficient classifier for $d > N$. Considering that MFCI does not employ daily financial market data which essentially determines the behavior of DFCI, it is particularly interesting to observe that they act similarly. This implicitly indicates that two types of economic crises (traditional and self-fulfilling crises) are closely correlated in real situations. More research is certainly desired to obtain further evidences supporting this hypothesis.

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