RISK ASSESSMENT FOR ENTERPRISE MERGER AND ACQUISITION VIA MULTIPLE CLASSIFIER FUSION

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ABSTRACT. This paper aims to solve the problem of Risk assessment for enterprise merger and acquisition (M&A), which is an important problem in modern company management. Firstly, we design an index system to assess risks of enterprise M&A behavior, and six risks are considered: 1) Systemic risk, 2) Law risk, 3) Financial risk, 4) Intermediary risk, 5) Integrated risk, and 6) Information risk. Furthermore, 18 indexes are chosen to cover these six aspects. Secondly, we illustrate how to utilize the proposed risk assessment in the decision system for enterprise M&A risk assessment. We separate the M&A risk assessment process to three steps, that is, 1) Before M&A, and 2) In M&A, and 3) After M&A. Particularly, after the risk assessment process, there are three decisions for enterprise managers, that is, 1) implement the original M&A plan, 2) modify the original M&A plan, and 3) refuse it. Thirdly, we propose the multiple classifier fusion based risk assessment algorithm, which aims to effectively combine the six support vector machines. To relax the limitation of the SVM classifier, we introduce the fuzzy theory in the multiple classifier fusion algorithm, and the category label assignment is determined by utilizing a maximum membership rule. Finally, we conduct an experiment to make performance evaluation by constructing a dataset which includes the M&A data of 200 enterprises, among which 185 enterprises are used as training dataset and others are regarded as testing dataset. Using ROC curve, MAE and MAPE as evaluation criterions, performance of the proposed method is compared with single SVM scheme. Experimental results demonstrate that combining multiple the SVM classifiers together, accuracy of M&A risk assessment is greatly enhanced.

1. Introduction. With the rapid development of the society economic, it is more and more difficult for enterprises to satisfy the high expansion speed in modern society. Particularly, under the condition of marketing economy, merger and acquisition may greatly influence enterprises’ growth, and may bring opportunity and profit to enterprise as well[4]. However, the process of enterprise’s merger and acquisition is full of risk. In recent years, we find that only a few parts of companies have obtained success in the process of merger and acquisition, and most cases of merger and acquisition have encountered many difficulties[5].

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It is well known that merger and acquisition of enterprise includes great risks when it provides opportunity and income to companies. After analyzing many cases of merger and acquisition, we find that failure rate of this process is greater than 50%, which makes the enterprises suffering great economic loss[17, 18]. Merger and acquisition risk is the main element to lead the failure of mergers and acquisitions and enhance costs of management. Considering the characteristics of enterprise merger and acquisition in some specific cases, merger and acquisition is a high-risk, capital management behavior due to a variety of uncertainties. Hence, it is of great importance for policy makers to discovery the risks in the process of merger and acquisition.

Merger risk assessment first is based on a detailed understanding of the basis of the composition of the merger and acquisition risk, followed to the various stages of the merger and acquisition risk identification, set up merger and acquisition risk index system, and finally sucked the merger and acquisition risks as a system, the use of mathematical methods knowledge uncertainty measure system information[1]. Effective merger and acquisition risk assessment can give a lot of favorable supports for merger and acquisition decision, and it is a crucial section of the merger and acquisition risk management with many difficulties. Hence, to discover the utilization of quantitative approaches to evaluate the risk of mergers and acquisitions has important practical significance to promote the risk management of corporate mergers and acquisitions[7, 15].

Therefore, in this paper, we aim to solve the problem of assessing enterprise merger and acquisitions risks utilizing the multiple classifier fusion. As the single classifier has many limitations, we introduce the multiple classifiers to tackle this problem. Particular, the main work of this paper lies in that how to effectively fuse these multiple classifiers. Main innovations of this paper lies in the following aspects:

1) We design an index system to assess risks of enterprise M&A behavior, and six risks are considered.

2) We discuss how to exploit the proposed risk assessment in the decision system for enterprise M&A risk assessment.

3) We propose a novel multiple classifier fusion based risk assessment algorithm to integrate the given six support vector machines.

The rest of this paper is organized as follows. Section 2 introduces the related works about the multiple classifiers fusion problem. Section 3 provides the overview of the enterprise merger and acquisition risk assessment problem. In section 4, the proposed multiple classifier fusion based risk assessment approach for enterprise merger and acquisition is given. In section 5, experiments are designed to make performance evaluation using the dataset collected from 200 enterprises. Finally, we conclude the whole paper in section 6.

2. Related works. As the single classifier has many limitations, fusion of multiple classifiers has been widely used in many machine learning and pattern recognition applications. Hence, in this section, we will analyze how multiple classifiers fusion is used.

Ma et al. proposed a novel objected-oriented technology which integrates pixel-based classification and a segmentation method to classify polarimetric synthetic aperture radar images. In this classification algorithm, a soft voting scheme is
exploited to combine multiple classifiers. Experiments results demonstrate that this method can solve the problem in majority voting[11].

Liu et al. proved that feature selection and multiple classifier fusion are effective to enhance the accuracy of land cover classification. Particularly, this paper integrated phenological metrics and multiple classifier fusion map land cover kinds in Jiangsu of China. Moreover, eight phenological metrics were proposed, and a multiple classifier fusion algorithm was proposed through integrating majority vote and the measurement of posterior probabilities together[10].

Islam et al. proposed a novel feature and score fusion based iris recognition method where voting approach on Multiple Classifier Selection technology has been exploited. Particularly, four discrete Hidden Markov Model classifiers output is integrated utilizing voting approach to obtain the recognition results. In this paper, the authors used CASIA-IrisV4 database to evaluate the performance of the proposed system in different dimensions[3].

Wang et al. proposed a highly effective fusion algorithm to enhance the performance of a multiple two-class classifiers system. The outputs of component classifiers are represented by a set of intuitionistic fuzzy values in advance, and then the fusion process is regarded as aggregation of intuitionistic fuzzy information. Furthermore, this method contains three different types of operators, that is, 1) intuitionistic fuzzy arithmetic average operator, 2) intuitionistic fuzzy weighted average operator and 3) intuitionistic fuzzy ordered weighted average aggregation operator[16].

To promote breast cancer risk stratification, Lederman et al. utilized three classifiers, such as artificial neural network, support vector machine, and Gaussian mixture model to forecast the likelihood of each woman to be recommended for biopsy independently. The performances of these three classifiers were compared, and seven fusion approaches for combined these classifiers were studied[6].

Gi et al. propose a novel query-by-humming system using the score level fusion of multiple classifiers. The main innovations of this paper lie in the following aspects: 1) three local classifiers are utilized, which are a) quantized binary code-based linear scaling, b) pitch-based dynamic time warping, and c) LS are exploited, 2) local maximum and minimum point-based LS is utilized as global classifiers, 3) the integration of local and global classifiers using the score level fusion based on the PRODUCT rule is exploited to obtain improved matching accuracy[12].

Li et al. presented a wavelet-based denoising approach and a Dempster-Shafer classification fusion method, and used them in the application in an e-nose system. Particularly, six transient-state features are obtained from the sensor devices filtered by the wavelet denoising method and are utilized to train multiple classifiers, which are 1) multilayer perceptrons, 2) support vector machines, 3) k-nearest neighbors, and 3) Parzen classifier. Particularly, The Dempster-Shafer technology is exploited to integrate all these classifiers to obtain the final results[9].

Rasheed et al. proposed a multi-classifier fusion method for motor unit potential sorting in electromyographic signal decomposition in order to obtain a better classification performance. In this paper, three types of classifiers are utilized: 1) certainty, 2) adaptive certainty, and 3) adaptive fuzzy k-NN. Experimental results show that, the classifier fusion methods can obtain better classification accuracy[14].

Huenupan et al. used the multiple classifier fusion technology to solve the speaker verification problem[2], Mahmoudi et al. introduced the multiple classifier fusion
in the field in voice disorder for children with cochlear implantation and hearing aid[19]. Other typical works about multiple classifier fusion please refer to references[8, 13, 20].

Different from the above papers, in this paper, we will try to use the multiple classifier fusion technology to solve the enterprise M&A risk assessment problem. As far as we know that multiple classifier fusion has not been used in this problem, hence, it is very meaningful for us to study this problem.

3. Overview of the enterprise merger and acquisition risk assessment problem. To solve the problem of risk assessment for enterprise merger and acquisition, the index system should be determined in advance. In this section, we design an index system to assess risks of enterprise merger and acquisition, and six aspects are included in our index system (shown in Fig.1), which are: 1) Systemic risk, 2) Law risk, 3) Financial risk, 4) Intermediary risk, 5) Integrated risk, and 6) Information risk. Particularly, 18 indexes are chosen to cover the above six aspects, and the following method is designed based this index system.

In economics, risk represents the dispersion of results. Therefore, we define the enterprise merger and acquisition risk as the dispersion degree when the merger and acquisition behavior has happened. The characteristics of dispersion variance are usually used to represent the fluctuation degree. The larger fluctuation means there is a greater risk. \( V \) refers to the standard deviation of enterprise profit value and it can be computed by the following equation.

\[
V = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (Z_t - \mu)^2 \cdot \rho_t}
\]  

(1)

where \( Z_t \) and \( \rho_t \) refer to the value of enterprise profit and the probability of realizing this profit rate. Parameter \( \mu \) denotes expectation of enterprise profit, and it is calculated as follows.

\[
\mu = \frac{1}{n} \cdot \sum_{i=1}^{n} Z_t \cdot \rho_t
\]  

(2)

Based on the above index system and theory analysis, the framework of the decision system for enterprise merger and acquisition risk assessment is illustrated in Fig. 2. In this framework, we divide the whole M&A risk assessment process in to three steps, that is, 1) Before M&A, and 2) In M&A, and 3) After M&A. Afterwards, we set six SVM classifiers to classify the given six types of risks in M&A process, and then the risk value can be computed by fusing the output of the given six SVM classifiers. Next, by comparing with the objective values, some M&A decisions can be obtained, and there are three decisions for the enterprise managers: 1) Implementing the merger and acquisition behavior, 2) Modifying the merger and acquisition plan, 3) Finishing the merger and acquisition behavior. Particularly, if the merger and acquisition plan should be modified, we use this framework to find a better plan.

4. The proposed multiple classifier fusion based risk assessment method for enterprise merger and acquisition. In this paper, we use several SVMs to construct the multiple classifiers based risk assessment system. Supposing there are a set of training samples which are \( T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\} \), where the
Figure 1. Index system for the risk assessment for enterprise merger and acquisition
conditions $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$ are satisfied. When giving the number $i$, a regression model is defined which can illustrate the relation between $x_i$ and $f(x_i)$:

$$f(x_i) = w \cdot x_i + b, \quad b \in \mathbb{R}, \quad i \in \{1, 2, \cdots, l\}$$  

(3)
To calculate the parameter \( y_i \) for \( x_i \), the constrained optimization problem can be tackled by the following equation.

\[
\min_{w,b,\xi^{(s)},\varepsilon} \tau(w,\xi^{(s)},\varepsilon) = \frac{\|w\|^2}{2} + C \cdot \left( \frac{\sum_{i=1}^l (\xi_i + \xi_i^*)}{l} + v \cdot \varepsilon \right)
\]

s.t.

\[
(w \cdot x_i + b) - y_i \leq \varepsilon + \xi_i \\
y_i - (w \cdot x_i + b) - \xi_i^* \leq \varepsilon
\]

where \( \xi^{(s)} \) and \( \varepsilon \) are larger or equal to zero. \( w \) and \( x_i \) denote D dimensional column vectors. \( v \) is in the range of \((0,1]\), and \( v \) is exploited to modify the number of support vectors. Moreover, \( \varepsilon \) is used to adjust the size of tube, and \( C \) means the trade-off value between separate margin and errors. The condition \( \xi^{(s)} = (\xi_1,\xi_1^*,\xi_2,\xi_2^*,\ldots,\xi_l,\xi_l^*)^T \) is satisfied, which refers to the slack variables.

In this paper, the M&A risk assessment is belonged to the linear separable problem, hence, SVM should meet the condition as follows.

\[
\begin{align*}
\{ & \begin{array}{ll}
w^T x_i + b \geq 1, & y = 1 \\
w^T x_i + b \leq -1, & y = -1
\end{array} \\
& \text{Assuming that } \{x_1,x_2,\ldots,x_N\} \text{ is a set of feature vectors, then we construct a training dataset and supposing that } \{\lambda_1,\lambda_2,\ldots,\lambda_N\} \text{ is a set of classification labels. If } x_n \text{ is regarded as an input to each classifier, a probability matrix can be obtained.}
\end{align*}
\]

\[
D(x_n) = \begin{bmatrix}
d_{1,1}(x_n) & d_{1,2}(x_n) & \cdots & d_{1,C}(x_n) \\
d_{2,1}(x_n) & d_{2,2}(x_n) & \cdots & d_{2,C}(x_n) \\
\vdots & \vdots & \ddots & \vdots \\
d_{L,1}(x_n) & d_{L,2}(x_n) & \cdots & d_{L,C}(x_n)
\end{bmatrix}
\]

where \( d_{l,c}(x_n) \) refers to the probability of the \( l^{th} \) classifier which is related to the \( c^{th} \) class. Based on the above analysis, we design to a function to combine the output of each classifier as follows.

\[
R_c = \Theta(d_{1c},d_{2c},\ldots,d_{Lc})
\]

where the function \( \Theta() \) is the classifier fusion function, and \( R_c \) is the result of classifier fusion.

For two classes \( c_1 \) and \( c_2 \), we integrate them to a new class \( \{c_1,c_2\} \), and then output probability \( d_{l,c}(x_n) \) means the belief value to the classifier \( \{c_1,c_2\} \). Considering the focal elements are the posterior probability of multiple classes, and the Eq. 8 can be rewritten as follows.

\[
E(x_n) = \begin{bmatrix}
A_{1,1}(x_n) & A_{1,2}(x_n) & \cdots & A_{1,C}(x_n) \\
A_{2,1}(x_n) & A_{2,2}(x_n) & \cdots & A_{2,C}(x_n) \\
\vdots & \vdots & \ddots & \vdots \\
A_{L,1}(x_n) & A_{L,2}(x_n) & \cdots & A_{L,C}(x_n)
\end{bmatrix}
\]

where \( C_i \leq C, \ i \in \{1,2,\ldots,L\} \) refers to the class number of the \( l^{th} \) classifier. Supposing that \( x \in \mathbb{R}^p \) means a feature vector and the vector \( \{1,2,\ldots,c\} \), and then each classifier can be represented as a mapping process as follows.

\[
M : \mathbb{R}^p \rightarrow \{1,2,\ldots,c\}
\]
To relax the limitation of the SVM classifier, we introduce the fuzzy theory in this paper. Hence, we define the fuzzy classifier as follows.

\[ \tilde{M} : \mathbb{R}^p \rightarrow [0, 1]^c \]  

with the vector \( \mu_{\tilde{M}}(x) = [\mu_{1,\tilde{M}}(x), \mu_{2,\tilde{M}}(x), \ldots, \mu_{c,\tilde{M}}(x)]^T \) as the output, where \( \mu_{i,\tilde{M}}(x) \) denotes the support provided by the classifier \( \tilde{M} \) under the hypothesis of the \( i^{th} \) classifier. Afterwards, using the maximum membership rule, the label assignment is determined as follows.

\[ \mu_{\text{max}}(\tilde{M}(x)) = \max_{j \in \{1, 2, \ldots, c\}} \mu_j(\tilde{M}(x)) \]  

Then the category which the feature vector \( x \) is belonged to is set to \( \mu_{\text{max}}(\tilde{M}(x)) \). Then, we use \( c_i(x) \) to represent the output of the \( i^{th} \) classifier, that is, \( c_i(x) = [d_{i,1}(x), d_{i,2}(x), \ldots, d_{i,c}(x)]^T \), \( 0 \leq d_{i,j}(x) \leq 1 \). Thus, the single classifier decisions can be fused by a fuzzy classifier by the fusion process as follows.

\[ \widetilde{M}(x) = RL(c_1(x), c_2(x), \ldots, c_L(x)) \]  

where \( RL \) is also named as an aggregation rule.

The decision template of the \( i^{th} \) class is the \( L \times c \) matrix \( F_i = \{f_i(k,s)\} \), of which the element is calculated by the following equation.

\[ f_i(k,s) = \frac{\sum_{j=1}^{N} \Phi(z_j,i) \cdot d_{k,s}(z_j)}{\sum_{j=1}^{N} \Phi(z_j,i)} \]  

where the function \( \Phi(z_j,i) \) denotes a function, the value of which is equal to 1 if the label \( i \) is belonged to \( z_j \), otherwise it is set to zero.

5. Experiment.

5.1. Evaluation criterion. To verify the performance of the multiple classifier fusion, some evaluation criterions are commonly used. In this paper, the following evaluation criterions are utilized in this experiment.

1) True positive (TP) means the number of true elements is classified as positive.
2) False positive (FP) means the number of false elements is classified as positive.
3) False negative (FN) means the number of false elements is classified as negative.
4) True negative (TN) means the number of true elements is classified as negative.
5) Mean absolute error (MAE), given \( N \) historical data \( y_t \) for \( t = 1 \) to \( N \), MAE is defined as follows.

\[ MAE = \frac{1}{N} \cdot \sum_{t=1}^{N} |y_t - \hat{y}_t| \]  

where \( \hat{y}_t \) denotes the forecasted result.
6) Mean absolute percentage error (MAPE) is represented as follows.

\[ MAPE = \frac{1}{N} \cdot \sum_{t=1}^{N} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \]
5.2. Experimental dataset and settings. In this section, we testify the effectiveness of the proposed method by constructing a dataset which includes the merger and acquisition data of 200 enterprises. In this dataset, we choose 185 enterprises as the training dataset, and others are regarded as the testing dataset. Particularly, the 15 samples in the testing dataset are shown in Table.1.

Table 1. Description of the testing dataset

|   | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 | E9 | E10 | E11 | E12 | E13 | E14 | E15 |
|---|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|
| f1 | .45 | .49 | .59 | .46 | .40 | .57 | .53 | .59 | .52 | .48  | .57  | .60  | .51  | .59  | .56  |
| f2 | .36 | .44 | .57 | .35 | .45 | .31 | .42 | .44 | .35 | .33  | .52  | .30  | .48  | .43  | .47  |
| f3 | .73 | .71 | .78 | .73 | .79 | .76 | .78 | .72 | .70 | .74  | .73  | .73  | .79  | .71  |     |
| f4 | .42 | .61 | .65 | .56 | .67 | .79 | .43 | .41 | .45 | .54  | .46  | .50  | .57  | .47  | .42  |
| f5 | .25 | .25 | .36 | .26 | .20 | .33 | .37 | .30 | .39 | .30  | .25  | .22  | .33  | .32  |     |
| f6 | .79 | .59 | .49 | .73 | .55 | .82 | .63 | .64 | .64 | .42  | .58  | .45  | .51  | .69  | .67  |
| f7 | .39 | .35 | .32 | .20 | .27 | .21 | .30 | .34 | .32 | .26  | .33  | .39  | .22  | .25  | .26  |
| f8 | .45 | .49 | .58 | .55 | .41 | .56 | .64 | .66 | .41 | .59  | .49  | .50  | .47  | .46  | .62  |
| f9 | .88 | .65 | .76 | .81 | .72 | .84 | .90 | .66 | .89 | .90  | .87  | .67  | .83  | .78  | .66  |
| f10| .43 | .43 | .56 | .46 | .43 | .59 | .46 | .48 | .46 | .54  | .43  | .55  | .42  | .53  | .43  |
| f11| .48 | .49 | .33 | .23 | .49 | .38 | .31 | .20 | .41 | .36  | .27  | .29  | .23  | .32  | .38  |
| f12| 1   | 1   | 0   | 0   | 0   | 1   | 1   | 1   | 0   | 1    | 1    | 0    | 0    | 0    |     |
| f13| .81 | .72 | .86 | .86 | .66 | .76 | .66 | .64 | .87 | .72  | .89  | .83  | .88  | .66  | .79  |
| f14| .40 | .49 | .64 | .65 | .67 | .73 | .69 | .54 | .50 | .46  | .73  | .54  | .71  | .68  | .72  |
| f15| .36 | .34 | .40 | .48 | .39 | .46 | .38 | .38 | .48 | .47  | .42  | .43  | .33  | .31  | .45  |
| f16| .47 | .50 | .40 | .44 | .46 | .46 | .48 | .59 | .44 | .55  | .57  | .59  | .45  | .50  | .40  |
| f17| .55 | .62 | .48 | .86 | .67 | .76 | .79 | .48 | .62 | .64  | .80  | .67  | .86  | .83  | .72  |
| f18| .87 | .98 | .89 | .72 | .92 | .95 | .68 | .98 | .76 | .91  | .88  | .96  | .93  | .89  | .97  |

As is shown in Table.1, each sample represents an enterprise with 18 indexes. Next, after training the multiple classifiers and fusing them, the risk value of these samples in the testing dataset can be achieved.

5.3. Performance analysis. In this experiment, we use six SVM classifiers to classify the six types of risk, and the process flowchart is illustrated in Fig.3. Particularly, SVM 1 to SVM 6 are used to solve Systemic risk, Law risk, Financial risk, Intermediary risk, Integrated risk, and Information risk respectively.

Next, we fuse proposed multiple classifiers the estimate the risk value of enterprise merger and acquisition, and the results are shown in Table. 2 (Enterprises are ranked by descending order).

To compare the performance of our algorithm with other schemes, we let expert assessment as the ground truth and also use the six SVM classifiers in Fig.3.

From Fig.4, we can find that compared with others methods, our proposed algorithm can assess the M&A risk more close to the expert assessment, and the average risk assessment error is given in Table. 3. Error rates our proposed algorithm is much lower than all single SVM classifiers.

Afterwards, we use the MAE and MAPE to test the performance of our algorithm and other single classifier schemes. In particular, we set the M&A risk to three categories: 1) Low, 2) Medium, 3) High, 4) Very High.

Results from Table.4 show that for the given four risk levels, the values of both MAE and MAPE are higher our method. Next, another performance evaluation metric – ROC curve is utilized for our method and the single SVM schemes. The
Figure 3. Settings of the multiple classifier fusion in this experiment

Table 2. Risk values of merger and acquisition for different enterprises

| Enterprise No. | Risk value |
|----------------|------------|
| E4             | 0.4437     |
| E5             | 0.4398     |
| E13            | 0.4374     |
| E15            | 0.4314     |
| E10            | 0.4232     |
| E3             | 0.4216     |
| E14            | 0.4187     |
| E9             | 0.4131     |
| E1             | 0.4120     |
| E2             | 0.4036     |
| E7             | 0.3896     |
| E12            | 0.3895     |
| E8             | 0.3868     |
| E6             | 0.3835     |
| E11            | 0.3644     |

Table 3. Average risk assessment error rates for different methods

| Method | SVM 1 | SVM 2 | SVM 3 | SVM 4 | SVM 5 | SVM 6 | Our algorithm |
|--------|-------|-------|-------|-------|-------|-------|---------------|
| Error rate | 14.7 | 9.8   | 9.2   | 17.4  | 12.1  | 18.6  | 5.5           |

ROC curve can describe the relationship between the true positive fraction and false positive fraction with the variations of decision threshold. Furthermore, the area under the ROC curve (denoted as AUC), is an effective index for evaluating classification results.
Table 4. Performance evaluation using MAE and MAPE

| Method | Low | Medium | High | Very high |
|--------|-----|--------|------|-----------|
|        | MAE | MAPE   | MAE  | MAPE      | MAE | MAPE |
| SVM 1  | 5.27| 29.54  | 3.21 | 6.73      | 8.66| 22.41|
| SVM 2  | 6.35| 26.76  | 3.08 | 8.51      | 6.73| 18.51|
| SVM 3  | 6.47| 28.40  | 3.68 | 9.08      | 8.06| 22.20|
| SVM 4  | 6.58| 27.33  | 3.79 | 9.64      | 8.06| 22.20|
| SVM 5  | 6.35| 30.11  | 3.28 | 8.89      | 8.17| 17.43|
| SVM 6  | 4.79| 30.06  | 2.97 | 8.31      | 7.58| 17.65|
| Our algorithm | 3.12| 23.54 | 1.97 | 6.89      | 4.59| 15.65|

Fig. 5 shows the ROC curves for the above methods, and the AUC value of our proposed method is larger than other single SVM classifiers. Integrating all the above experimental results together, we can see that our proposed method achieves considerable successes in the classification of M&A risks, that is, our method can effectively assess the M&A risks. Particularly, experimental results demonstrate that fusing the six SVM classifiers by our method, the accuracy of risk assessment can be obviously promoted. The reason why the proposed algorithm can achieve better performance mainly lies in that we introduce the fuzzy theory to relax the limitation of the SVM classifier.

6. Conclusion. In this paper, we propose a novel enterprise merger and acquisition risk assessment approach based on multiple classifier fusion. An index system to assess risks of enterprise M&A behavior is designed in advance, including: “Systemic risk”, “Law risk”, “Financial risk”, “Intermediary risk”, “Integrated risk”, and “Information risk”. Moreover, we explain how to use the proposed risk assessment in the decision of enterprise M&A behavior. Afterwards, we provide a multiple classifier fusion based risk assessment algorithm to integrate the six support vector machines. Particularly, we introduce the fuzzy theory in the multiple classifier
fusion algorithm in order to relax the limitation of the SVM classifier. In the end, experimental results demonstrate the effectiveness of the proposed algorithm.

In the future, we will try to extend the proposed works in two aspects: 1) We will discuss how to optimize the parameters of SVM classifier by optimization algorithm, and 2) We will enlarge experimental dataset for enterprise merger and acquisition.

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