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A Novel Classification Method based on Improved SVM and its Application

Senhua Wang[1] and Rui Li [2]*

[1]*School of Economic and Managment, Beihang University, Beijing 100191 China*
[2] *School of Business, Beijing Normal University, Beijing 100875 China*

Abstract

Support vector machine is a machine learning method. It takes on the good generalization ability and prediction accuracy. But the parameters of SVM model seriously affect the generalization ability and prediction accuracy of SVM model on the great extent. So an improved particle swarm optimization (PSO) algorithm based on chaotic search is introduced into the SVM model in propose a novel data classification (AMPSVM) method for processing the complex data. The first, the ergodicity, stochastic property, and regularity of chaos is used to chaotically search the current best individual, which randomly replaces the selected individual in the population in order to speed up evolution, improve the searching ability, convergence speed and accuracy. Then the improved PSO algorithm is used to select and optimize the parameters of the SVM (AMPSVM) model in order to improve the learning performance and generalization ability of the SVM model. In order to verify the effectiveness of the AMPSVM method, UCI data is selected in here. The experiment results show that the proposed AMPSVM method takes on the strong generalization ability, best sensitivity and higher classification accuracy.

Keywords: *Particle swarm optimization; chaotic search; support vector machine; data classification; optimization performance*

1. Introduction

Classification is one of the most widely used technologies in data analysis. It has become more and more important [1]. With the research of data analysis, more and more data classification algorithms have been proposed. Classification is to construct a classifier according to the characteristics of the data set, then the classifier is used to give a category for the unknown data. That's to say, the classification refers to select already categorized training set form the data, the classification techniques are used to establish the classification model on the selected training set in order to classify the uncategorized data. The kind of classification algorithms has a wide range of applications, can further derive prediction algorithm. The process of constructing classifier is generally divided into two steps of training and classifying. In the process of training, the characteristics of the training data set are analyzed and selected, then an accurate description or model of the corresponding data set is generated for each category(classifier). In the process of classifying, the description or model of category is used to classify the uncategorized data in order to determine the category of the uncategorized data, and the accuracy of the classification is calculated [2].

At present, the main classification algorithms are divided into two parts: supervised learning classification algorithms and semi-supervised learning classification algorithms [3-4]. The most mainstream classification algorithms are Naive Bayesian classification algorithm, decision tree classification algorithm, neural network classification algorithm, support vector machine classification algorithm, random forest classification algorithm and Adaboost classification algorithm and so on. Ciesielski et al. [5] proposed a

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classification of the data of the process of starch saccharification based on the self-organizing maps. Several configurations of the neural networks were tested obtaining an explicit division of process data into 3 classes of objects. Dong et al [6] proposed an approach to the classification of radar images based on two steps. First an image is partitioned into uniform areas (segments), and then these segments are classified. Peters et al. [7] proposed a rough set approach to classifying meteorological volumetric radar data in order to detect storm events responsible for summer severe weather. Price et al. [8] described the use of classification trees for BST and included discussion of its principal parameters and features. Belacel et al. [9] proposed a new methodology for learning parameters of multiple criteria classification method PROAFTN from data. Mastrogiannis et al. [10] proposed a method called CL.E.D.M. (CLassification through ELECTRE and Data Mining), that employs aspects of the methodological framework of the ELECTRE I outranking method, and aims at increasing the accuracy of existing data mining classification algorithms. Luengo and Herrera [11] studied the behavior of a fuzzy rule based classification system and its relationship to data complexity, and proposed a case of study the fuzzy hybrid genetic based machine learning method. Babaoglu et al.[12] proposed a novel hybrid method based on particle swarm optimization with k-nearest neighbor classifier (PSOkNN). Yu [13] developed a new support vector clustering (SVC)-based probabilistic approach for unsupervised chemical process monitoring and fault classification. Kemal [14] proposed a binary encoded output based data weighting (BEOBDW). To generalize the proposed data weighting method, five datasets have been used. Li et al. [15] proposed a SVM classification method based on cluster boundary sampling and sample pruning. Wang and Shi [16] proposed a density-weighted under-sampling method for SVM on imbalanced data. Liu et al. [17] proposed a twin support vector machine (TWSVM) in order to solve the shortages of the large calculation amount and slow classification speed of SVM. And an automatic classification method of star spectra data based on manifold fuzzy twin support vector machine (MF-TSVM) is proposed. Cao et al. [18] proposed a novel fast feature selection method based on multiple SVDD and applied it to multi-class microarray data.

For these proposed data classification methods, although they can better realize the data classification, but the classification accuracy is not high, and classification speed is lower. In allusion to the existing shortcomings of classification methods, an improved particle swarm optimization(PSO) algorithm is introduced into the SVM model in propose a novel data classification(AMPSVM) method for improving the learning performance and generalization ability of the SVM model and realizing data classification.

2. Basic Methods

2.1. Chaos

Chaos is an interesting nonlinear dynamics, which take on many outstanding properties, such as randomicity, ergodicity, sensibility and so on[19]. So there is a significant interest in constructing optimization methods based on chaotic search routines in the past 20 years. For example, chaotic simulated annealing, chaotic particle swarm optimization, chaotic Tabu search, and so on. There are some ant-inspired optimization algorithms based on the non-deterministic probability theory. These optimization algorithms have obtained many achievements in computer science in recent years. However, Cole suggested that ant colony takes on a periodic behavior, while single ant shows chaotic activity patterns. That is to say "The existence of chaos in animal behaviors can have several important implications. Variation in the temporal component of individual behavior may not be due simply to chance variations in the stochastic world, but to deterministic processes that depend on initial conditions." So the models play a very important role in understanding the underlying the dynamics of biological systems.

In general, the chaos is obtained random motion state by the deterministic equation, and the chaotic variable is the chaos variable with chaos state. Logistic equation is a typical chaotic system [20]:

$$z_{n+1} = \mu z_n(1 - z_n) \quad n = 0,1,2,3,\cdots \tag{1}$$

where μ is control parameter, the equation can be considered as a dynamical system. After the value of μ is determined, a determined time series $z_1, z_2, z_3, \cdots$ is obtained by the arbitrary initial values $z_0 \in [0,1]$. In a certain range, a chaotic variable has the following characteristics: randomness, its performance is as messy as random variables; ergodicity, it may not repeat all the states of the space; regularity, the variable is derived by the determined iterative equation. The chaotic search is a novel optimization method, it makes use of the unique ergodicity of chaotic system to achieve a global optimization. And it does not require the objective function with the characters of continuity and differentiability.

2.2. Particle Swarm Optimization Algorithm

The PSO algorithm [21] is a search algorithm based on the simulation of the social behavior of birds within a flock. In PSO algorithm, individuals, referred to as particles, are "flown" through hyper dimensional search space. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity (v) and position(x) of each particle will be changed by the particle best value (pb) and global best value (gb). The velocity and position updating of the particle is shown:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1\left(pb_{ij}(t) - x_{ij}(t)\right) + c_2 r_2\left(gb_{ij}(t) - x_{ij}(t)\right) \tag{2}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{3}$$

Where $v_{ij}(t+1)$, velocities of particle i at iterations j, $x_{ij}(t+1)$, positions of particle i^{th} at iterations j^{th}. w is inertia weight. t denotes the iteration number, c_1 is the cognition learning factor, c_2 is the social learning factor, r_1 and r_2 are random numbers uniformly distributed in [0, 1]. Thus, the particle flies through potential solutions towards pb and gb in a navigated way while still exploring new areas by the stochastic mechanism to escape from local optima. Generally, the value of each component in v can be clamped to the range $[-v_{\max}, v_{\max}]$.

2.3. Support Vector Machine(SVM)

Support vector machine (SVM), introduced by Vapnik is one of the popular tools for a supervised machine learning method based on structural risk minimization [22]. The basic characteristic of SVM is to map the original nonlinear data into a higher-dimensional feature space where a hyperplane is constructed to bisect two classes of data and maximize the margin of separation between itself and those points lying nearest to it (the support vectors). The hyperplane should be used as the basis for classifying unknown data.

The Given the training sample is $S = \{(x_i, y_i) \mid i = 1,2,3,\cdots,m\}$, m is the number of samples, the set $\{x_i\} \in R_n$ represents the input vector, $y \in \{-1,1\}$ indicates the corresponding desired output vector, the input data is mapped into the high dimensional feature space by using nonlinear mapping function $\phi(\bullet)$. Then the existed optimal classification hyper plane must meet the following conditions:

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = 1 \\ \omega^T x_i + b \leq -1, & y_i = -1 \end{cases} \tag{4}$$

where ω is Omega vector of super plane, b is offset quantity. Then the classification decision function is described as follow:

$$f(x_i) = \mathrm{sgn}(\omega^T x_i + b) \tag{5}$$

The classification model of SVM model is described by he optimization function $\min_{\omega,\xi,b} J(\omega,\xi_i)$:

$$\min_{\omega,\xi,b} J(\omega,\xi_i) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{m}\xi_i^2 \tag{6}$$

$$s.t.\quad y_i[\omega^T\phi(x_i)+b] = 1-\xi_i,\ i=1,2,3,\cdots,m \tag{7}$$

where ξ_i is slack variable, b is offset, ω is support vector, $\xi = (\xi_1, \xi_2, \cdots, \xi_m)$, γ is classification parameter for balancing the fitting error and model complexity.

The optimization problem transforms into its dual space. Lagrange function is introduced to solve it. The corresponding optimization problem of the SVM model with Lagrange function is:

$$L(\omega,b,\xi,\alpha) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{m}\xi_i^2 - \sum_{k=1}^{m}\alpha_i\{y_i[\omega^T\phi(x_k)+b]-1+\xi_i\} \tag{8}$$

where α_i is the Lagrange multiplier, and $\alpha_i \geq 0 (i=1,2,3.\cdots,m)$. The optimal conditions are described:

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum_{i=1}^{m}\alpha_i y_i \phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{m}\alpha_i y_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \Rightarrow \alpha_i = \gamma\xi_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \Rightarrow y_i(\omega^T\phi(x_i)+b)-1+\xi = 0_i \end{cases} \tag{9}$$

The following linear equation is obtained:

$$\begin{bmatrix} 0 & L^T \\ L & \Omega+\gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{10}$$

where $Y = [y_1, y_2, \cdots, y_m]^T \in R^m$, $L \in R^m$ is vector of the element m, $y^T = [y_1, y_2, \cdots, y_m]$, I is unit matrix, $I_m = [1,1,\cdots,1]^T$, $\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_m]^T$, $\Omega = [\Omega_{ij}]_{m\times m}$, $\Omega_{ij} = y_i y_j K(x_i, x_j)$. Then the classification decision function is described as follow:

$$f(x_i) = \mathrm{sgn}\left(\sum_{i=1}^{m}\alpha_i y_i K(x,x_i)+b\right) \tag{11}$$

There are several kernel functions, such as linear kernel function, polynomial kernel function, radial basis kernel function (RBF), Sigmoid kernel function and Fourier kernel function and so on. Because the RBF has the advantages of simple form, symmetry radial, good smoothness and analyticity and so on. So the RBF is selected to be regarded as kernel function of the SVM model. The specific express of the RBF is shown as follows:

$$K(x, x_i) = \exp[-(x - x_i)^2 / 2\sigma^2] \quad (12)$$

Kernel width (σ^2) and regularization parameter (γ) is two important parameters in the SVM model. Their selection directly influences the learning ability and generalization performance.

3. An Improved Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm is a search algorithm based on simulating the social behavior of birds. It is simple optimization algorithm that takes on fast search speed and high efficiency. But it is to easily fall into local extreme points, has the disadvantages of slow convergence and poor accuracy and so on in the late evolution. If one optimization method is used to further improve the quality of population in each generation, it will undoubtedly help the posterior search process. So the chaotic search idea is introduced into the PSO algorithm in order to propose a chaotic particle swarm optimization (CMPSO) algorithm. In the proposed CMPSO algorithm, the ergodicity of chaotic search is used to generate chaotic sequences based on the search for the optimal location by current whole particle swarm. The optimal position of particle in the generated chaotic sequences is used to randomly replace the position of one particle in current particle swarm.

The specific steps of the chaotic particle swarm optimization algorithm are as follows:

(1) Initialize parameters of the CMPSO algorithm

The CMPSO algorithm need initialize these parameters: population size (N), the cognition learning factor (c_1), the social learning factor(c_2),the number of maximum iteration($T_{\max}$),and chaotic search times(T_c).

(2) Randomly generate one population with N individuals.

(3) Calculate the fitness value

An evaluation function is determined to calculate the individual fitness value in the population according to solving optimization problem. Then each individual fitness value is calculated. The global optimum position of population is found. The best position is obtained by the comparing.

(4) Update speed of the particle

The velocity of the particle is updated according to the given expression(2).

(5) Update the position of the particle

The position of the particle is updated according to the given expression(3).

(6) Obtain the best feasible solution

The optimal positions $P_g = (p_{g1}, p_{g2}, p_{g3}, \cdots, p_{gn})$ is executed the chaotic search. The $p_{gi}(i = 1,2,3,\cdots,n)$ is mapped to the definition domain $[0,1]$ of Logistic equation:

$$z_i = \frac{p_{gi} - a_i}{b_i - a_i} \; i = 1,2,3,\cdots,n \quad (13)$$

Then, Logistic equation is used to generate the chaotic variable sequences $z_i^{(m)}(m = 1,2,\cdots)$ by executing iteration. The generated chaotic variable sequences $z_i^{(m)}(m = 1,2,\cdots)$ is returned to the original solution space by inverse mapping $p_{gi}^{(m)} = a_i + (b_i - a_i) z_i^{(m)}(m = 1,2,3,\cdots)$. Finally, the following equation is obtained:

$$p_g^{(m)} = (p_{g1}^{(m)}, p_{g2}^{(m)}, p_{g3}^{(m)}, \cdots, p_{gn}^{(m)})(m = 1,2,3,\cdots) \quad (14)$$

In the original solution space, the fitness value of each feasible solution $p_g^{(m)})(m = 1,2,3,\cdots)$ by using the chaotic variable is calculated. The best feasible solution p^* with retention performance is obtained.

(7) The best feasible solution p^* with retention performance is used to replace randomly selected one particle from the current population.

(8) Update iteration, $t = t + 1$ is implemented. If $t < T_{\max}$, then go to **(3),** otherwise stop.

(9) Output the optimal position of individual(pb) and the global optimal position of individual(gb) .

4. A Novel Data Classification (AMPSVM) Method

In the practical application, in order to obtain the SVM classifier with higher accuracy, all parameters of SVM model need be optimized. After the selected RBF is regarded as the kernel function, two parameters of regularization parameter (γ) and kernel parameter (σ^2) in a large extent determines the learning ability and prediction ability of SVM model. So the optimal combination of regularization parameter (γ) and kernel parameter (σ^2) need be searched.

At present, the optimal selection method for parameters of SVM model is grid search method. This method obtains the satisfactory result by executing continuous experiments. But this method consumes a lot of times and low efficiency. A gradient descent method is proposed to select the parameters of SVM model, but the method is restricted by differentiable kernel function, and easy to fall into the local minimum value in the search. At the same time, immune optimization algorithm is proposed to optimize the parameters of SVM model in order to reduce the blindness of selecting parameters and improve prediction accuracy. But the realization of this algorithm is complex. The genetic algorithm is used to determine the parameters of SVM model, but it need execute the crossover and mutation, and adjust several parameters, take on the complex computation and low efficiency. The PSO algorithm is a new algorithm based on swarm intelligence. It follows the optimal particle to search in the solution space, and takes on the parallel processing characteristic, good robustness, simple and easy realization and high computational efficiency. And it can find the global optimal solution of optimization problem according to the larger probability. But the PSO algorithm exits the easy falling into local extreme points, slow convergence and poor accuracy. Therefore, the proposed CMPSO algorithm with global search ability used to select and optimize the parameters of SVM model in order to obtain the more accurate and better SVM classifier (AMPSVM).

The implementation steps of the novel data classification (AMPSVM) method based on improved PSO algorithm and SVM model are shown as follows:

(1) The support vector is selected from the sample vector set in order to construct the training sample set S' .

(2) Each support vector in the training sample set can obtain the parameters of SVM classifier for forming a particle, in order to construct the population of particles S .

(3) Execute the proposed CMPSO algorithm. The steps are given in Section 4.

(4) The optimal position of individual (pb) and the global optimal position of individual (gb) are selected as the values of the parameters of SVM model classifier.

(5) When the number of iterations reaches the maximum iterations or the fitness function value meets the requirements of particle, the proposed AMPSVM method is terminated. The optimal AMPSVM method is obtained. Otherwise, return to **(3)**. to calculate until the number of maximum iteration is reached or the fitness function value meets the requirements of particle.

5. Experimental Results and Analysis

In order to test the classification performance of the proposed AMPSVM method, UCI data is select in this paper. UCI database is proposed by University of California, Irvine for machine learning database. The database includes a total of 187 data sets at present. The number of UCI database is increasing. The UCI database is a commonly used standard test data set. Five kinds of data sets(Pittsburgh Bridges, Wine, Libras Movement, Spectrometer and Arrhythmia) are selected from UCI database in this experiment. The detail describing of the data is shown in Table 1. The experiment works on Intel(R) i5, 2.40GHz, 2G RAM, Windows 8 and Matlab2012b. The experiment selects the different initial samples, which are regarded as the training sample to train the SVM and CMPSO algorithm. In this experiment, the particle sizes are 50, the maximum number of iterations are 500, the learning factor $c_1 = c_2 = 1.8$, the initial inertia weight $w = 0.3$,the penalty parameter $C = 150$, the value range of the radial basis kernel width is σ =[0,10], the value range of the regularization parameter is γ =[1,1000]. The RBF kernel function is selected as the kernel function.

Table 1. The Detail Describing of the Data

Index	Data set	Samples	Dimensions
1	**Pittsburgh Bridges**	108	13
2	**Wine**	178	13
3	**Libras Movement**	360	91
4	**Spectrometer**	531	102
5	**Arrhythmia**	452	279

In the classification experiment under the UCI data set, each method is run independently 30 times. In order to verify the classification performance of proposed AMPSVM method, the KPCA algorithm , KLDA algorithm, SVM algorithm, PSO-SVM algorithm are selected to compare their classification performances. The results are shown in Table 2.

Table 2. The Average Accuracy of Data

Index	Data set	Average accuracy(%)				
		KLDA	KPCA	SVM	PSO-SVM	AMPSVM
1	**Pittsburgh Bridges**	70.23	80.36	86.03	90.31	95.28
2	**Wine**	71.65	78.89	82.32	88.47	92.46
3	**Libras Movement**	72.64	78.06	85.02	87.08	91.37
4	**Spectrometer**	71.83	79.95	82.67	88.35	90.89
5	**Arrhythmia**	63.78	72.89	80.35	85.24	88.04

As can be seen from Table 2, for the different dimensions and different quantities of training data, the average classification accuracy of the proposed AMPSVM method is best result. The average accuracy is 95.28% for the data of Pittsburgh Bridges, 92.46% for the data of Wine, 91.37% for the data of Libras Movement, 90.89% for the data of Spectrometer and 88.04% for the data of Arrhythmia. Therefore, the classification effect of the proposed AMPSVM method is better than the KPCA algorithm, KLDA algorithm, SVM algorithm, PSO-SVM algorithm. The proposed AMPSVM method can quickly classify the UCI data set and takes on the strong generalization ability, best sensitivity and higher classification accuracy.

6. Conclusion

Support vector machine is a simple method to realize the pattern recognition. The SVM does not require a long training process. The optimal hyperplane is solved according to the initial sample. In this paper, the ergodicity, stochastic property, and regularity of chaos is used to improve particle swarm optimization (PSO) algorithm for obtaining CMPSO algorithm. Then the proposed CMPSO algorithm is used to select and optimize the parameters of the SVM(AMPSVM) model in order to improve the learning performance and generalization ability of the SVM model. And UCI data is selected to verify the effectiveness of the AMPSVM method. The experiment results show that the proposed AMPSVM method takes on the strong generalization ability, best sensitivity and higher classification accuracy.

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Authors

Senhua Wang, he is a Ph.D. Candidate, School of Economic and Managment Beihang University. The main research directions: Management Science and Engineering.

Rui Li, he is a Professor in the School of Business, Beijing Normal University. The main research directions: Financial.