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Analysis of Characteristics and Mineralization Process of Polymetallic Ore Deposit in South China

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Based on the analysis of the characteristics and mineralization process of the polymetallic ore deposit in South China, this paper applies the improved nonlinear technology (GA-SVM) to the metallogenic prognosis, and provides a new idea for the prediction of the favorable degree of mineralization. On the basis of the analysis of the South China ore district mineralization favorable degree, select 28 learning samples and 10 geological variables related to ore-forming. Support vector machine (SVM) method based on genetic algorithm(GA) is applied for the construction of the mineralization favorable model, and compare with the prediction results of BP neural network model. The results show that the GA-SVM regression model can well predict the nonlinear relationship between the favorable degree and the geological variables. When the number of samples are limited, GA-SVM has higher fitting precision than BP neural network, more suitable for nonlinear metallogenic prediction work. Metallogenic favorability analysis helps to understand the process of polymetallic deposit, with strong promotion significance.

1. Introduction

The establishment of mathematical models for metallogenic prognosis is an important means to search for concealed ore bodies. The commonly used nonlinear techniques, for example artificial neural network with nonlinear mapping, good fault tolerance and strong self-adaptation features and so on, are widely used in the field of metallogenic prediction. It is a kind of learning method based on large sample, and the adjustment of the network coefficient and initialization method has no theoretical guidance, the training process is easy to fall into local minimum, the convergence speed is slow, network structure is not stable and so on problems. SVM is a kind of machine learning algorithm developed from statistic theory in recent years (Cheng and Hu, 2013). It can effectively realize the accurate fitting of high dimensional nonlinear system based on small samples. Previous studies have accumulated a large amount of geological and mineral resources in South China ore concentration area, while it has not been reported that how to make the study of metallogenic prognosis by nonlinear fitting analysis of these multivariate information.

Metallogenic favorability analysis helps to understand the process of polymetallic deposit. In this paper, the metallogenic geological variables are selected, use genetic algorithm (GA) global search performance, to determine the optimal SVM kernel parameter and error penalty factor, construct favorable degree ore prediction model based on GA-SVM regression, and compare with BP neural network prediction results, so as to provide a new method for nonlinear metallogenic prediction, play a role of reference for the South China polymetallic concealed ore bodies.

2. Analysis on metallogenic favourable degree of south China ore concentration area

Many scholars have made a lot of researches on the geological structure, metallogenic regularity and genesis of South China ore area. The area constructs flysch formation in the Devonian Early Carboniferous, volcano clastic rocks and mafic volcano rock. The magma intrusion activity is strong in the area, which provides a favorable tectonic environment for the mineralization.

Based on the collected data, the characteristic analysis model is used to construct typical ore deposit characteristic model, and the quantitative prediction of the unknown region is realized by the degree of favorable mineralization. For the model unit data, use the product matrix principle component method in the analysis of characteristics to determine the weight coefficients corresponding to each variable, and carry out

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the formal transformation, and the sum as 1. Establish typical ore deposits features analysis model in this area, units metallogenic favorability are shown as follows (Xin et al, 2015):

Y=0.0826X1+0.1255X2+0.0478X3+0.1153X4+
0.1625X5+0.1001X6+0.0978X7+
0.0695X8+0.0529X9+0.1460X10 (1)

The model can be brought into the rest of the unit to find the favorable degree of mineralization of each unit.

3. GA-SVM theory

Support vector machine is a new method, which is proposed by Vapnik. It is based on rigorous mathematical theory, and it is the realization of VC dimension theory and structural risk minimization principle in statistical learning under the condition of limited samples. A sample training is set to contain N vectors of d- dimension feature space, $x_i \in$ Rd(i=1, 2, ...N), and the target $y_i \in$ {-1, 1} is associated with each vector x_i. Finding the optimal hyper plane problem is transformed into convex two-time equation, namely (Zhang et al, 2014):

$$\begin{cases} Minimize: \frac{1}{2}\|\omega\|^2 \\ Subject: y_i\left(\omega \bullet x_i + b\right) \geq 1, i = 1, 2, \ldots, \mathrm{N} \end{cases} \tag{2}$$

Among them, ω and b are on behalf of the coefficient of hyper plane equation f(x)=$\omega \bullet x + b$. According to convex two times programming solution in the optimization theory, Larange function is constructed, namely:

$$L\left(\omega, \alpha, b\right) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{N} \alpha_i y_i \times \left(\omega \bullet x_i + b\right) + \sum_{i=1}^{N} \alpha_i \tag{3}$$

In the formula, α_i (1, 2, ..., N) is the introduced Lagrange multiplier. By adding the error penalty factor c to the objective function, the threshold value is set, and the above equation is transformed into:

$$\begin{cases} Minimize: \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \times \alpha_i \alpha_j y_i y_j \left(x_i \bullet x_j\right) k\left(x_i \bullet x_j\right) \\ Subject: \sum_{i=1}^{N} \alpha_i y_i = 0, 0 \leq \alpha_i \leq c, i = 1, 2, \ldots, \mathrm{N} \end{cases} \tag{4}$$

$k\left(x_i \bullet x_j\right)$ is on behalf of the selected kernel function for the conversion of SVM from low dimensional space to high dimensional space. In simple terms, support vector machine is that the nonlinear transformation of the inner product function definition transforms the input space into a high dimensional space, and linear fitting is carried out in this space, to obtain the best fitting curve (Xie et al, 2014).

Genetic algorithm (GA) is a kind of optimization algorithm with strong robustness, and it is a method to search the optimal solution by simulating the natural evolution process. The mean square error (MSE) is considered as the basis for searching the optimal parameter, which is the best fitness in the theory of genetic algorithm. Genetic optimization steps are as follows: (1) determine the optimal vector, and the initial population is generated by GA; (2) use the initial population to carry out training on the training set, and the overall MSE is converted into GA fitness; (3) according to the fitness of GA, carry out selection, mutation and crossover operations on vector optimization, to produce the next generation; (4) repeat the population until the setting calculation ends, and obtain the optimal combination parameters.

4. Prediction of metallogenic favourable degree based on GA-SVM regression

Study selects includes 14 deposits (points) unit, 3 units and 11 non-mineralization occurrences unit, a total of 28 units (S1~S28) as the study samples. In the study samples, deposits (points) or mineralization points are randomly selected for 11 and no ore sample for 8, consist the training sample (19 units), and the remaining 9 units are taken as the validation samples. The training sample data is shown in Table 1. With the above 10 parameters (X1~X10) as the input layer of the SVM prediction model, and the favorable degree of mineralization is used as the model output layer.

Vapnik research shows that the performance of SVM is not greatly related to the type of kernel function selected . The kernel parameter g and the error penalty factor c are the main factors that affect the performance of SVM. The radial basis function (RBF) has only one control parameterε, and the fitting effect is better, so this paper uses the RBF kernel function as the basic function to map 10 input vectors into a high-dimensional Hilber space for analysis, so as to reduce the analysis complexity of the whole model. In order to make the model with high precision, use GA algorithm to carry out intelligent optimization selection of kernel parameter g and error penalty factor c in SVM algorithm.

Table 1: GA-SVM training sample data

Units No.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	Favorable degree
S1	1	0	0	1	1	1	1	1	1	1	0.8267
S3	0	1	1	1	1	1	0	1	0	0	0.6207
S4	0	1	1	0	1	0	0	1	1	1	0.6342
S6	0	1	0	0	1	0	0	1	1	1	0.5604
S7	0	0	1	1	1	0	1	0	0	1	0.5603
S9	1	1	0	1	1	1	1	0	0	1	0.8052
S10	1	1	0	0	1	0	1	0	0	1	0.6628
S12	1	0	0	0	1	0	0	0	0	1	0.3305
S13	0	0	1	0	1	0	0	0	0	1	0.3942
S16	1	0	0	0	0	1	0	0	0	1	0.3357
S17	1	1	0	0	0	0	0	1	0	1	0.4475
S18	1	0	0	0	0	0	0	0	0	0	0.0885
S19	0	1	0	0	0	0	0	0	0	1	0.2642

The genetic algorithm operation process parameters are selected as follows: randomly generate the initial population, the number of cross validation v is 5, the maximum genetic algebra (max.gen) is 100, the population individual number (sizepop) is 20, genetic gap (ggap) is 0.9, the search space for g and c is (0, 100), and the RBF kernel function parameterεis 0.01. The training samples are brought into the GA-SVM regression prediction model, and a stable iterative value of the best fitness is obtained through the 100 times evolutionary computation, as shown in Figure 1. From the fitness curves, it can be seen that after 58 times of iterative genetic, the population best fitness is basically stable, namely kernel parameter g and error penalty factor c obtaining the optimal solution, respectively 70.5241 and 0.0019, and the minimum mean square error MSE of training samples is 2.8236 * 10-4 (Zhao et al, 2014).

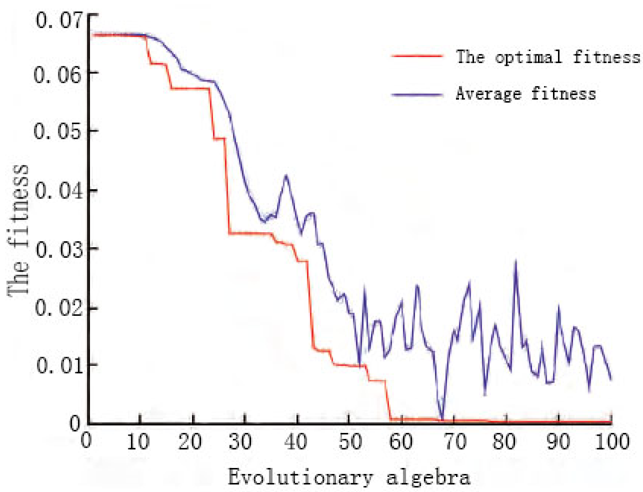

Figure 1: Process of genetic evolution

The training samples of the 19 groups are trained by the GA-SVM model, and the results are shown in Figure 2. The mean square error is 6.2657 * 10-5 (Cheng et al, 2014).

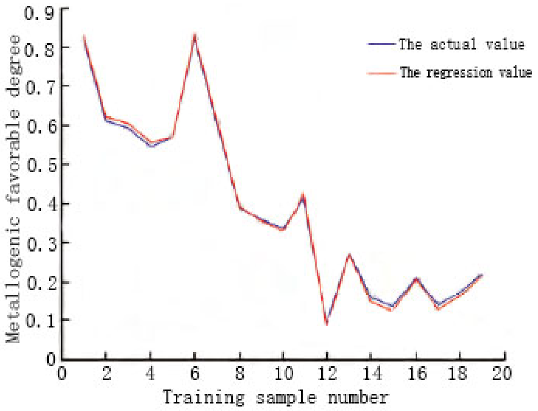

Figure 2: Training results of GA-SVM model

From the figure, it can be seen directly that the regression value is basically consistent with the actual value, proved that GA-SVM model can be applied in regression fitting of nonlinear relationship between the mineralization favorable degree and geological variables, and then it can carry out the next step for forecast. 9 test data in the study sample are brought into the prediction model of mineralization favorable degree based on GASVM regression. The model is calculated and the results are shown in Table 2, and the mean square error is close to zero (7.164 * 10-5). The absolute error between the predicted and the actual value is less than 0.01, which is in accordance with the requirement of the error of the metallogenic prediction (Cheng, 2015).

Table 2: GA-SVM model testing results

Validation units	The actual value	GA-SVM	The absolute error
S2	0.8298	0.8202	0.0096
S5	0.6494	0.6398	0.0096
S8	0.5239	0.5217	0.0022
S11	0.5035	0.4944	0.0091
S14	0.3911	0.3876	0.0035
S15	0.3287	0.3366	-0.0079
S22	0.1224	0.1326	-0.0102
S24	0.0826	0.0926	-0.0100
S26	0.1460	0.1557	-0.0097

Table 3: Evaluation index values of SVM and BP neural network

Evaluation indexes	BP neural network	GA-SVM
MAE	4.229%	0.798%
MAPE	9.624%	3.916%
ME	37.944%	12.107%
MSE	5.6×10^{-3}	0.081×10^{-3}

In order to better highlight the superiority of GA-SVM model in the prediction of the mineralization favorable degree compared to BP neural network, introduce several evaluation indicators: the average absolute error (MAE) of test data, the absolute value of the average relative error (MAPE), the maximum absolute relative error (ME), and the variance of the prediction error (MSE). The comparison of model parameters is shown in Table 3.

From Table 3, it can be seen that BP neural network and GA-SVM model has shown good nonlinear fitting ability in the prediction of favorable degree of mineralization. The comparison showed that the absolute error curve of GASVM is smaller than that of BP neural network, and the MAE, MAPE, ME and MSE of GA-SVM

model are all smaller than that of BP neural network. It fully reflects that the established GA-SVM model has better cognitive and generalization ability, and has a stronger stability in the metallogenic favorable degree regression prediction than the BP neural network, more suitable for mineralization favorable degree nonlinear prediction work (Watling et al, 2013).
This paper explores the effectiveness of the nonlinear metallogenic prediction method (GA-SVM), and provides decision-making basis for further detailed geological surveys work, as shown in Figure 3, having certain promotion significance in work on metallogenic prediction in other regions.

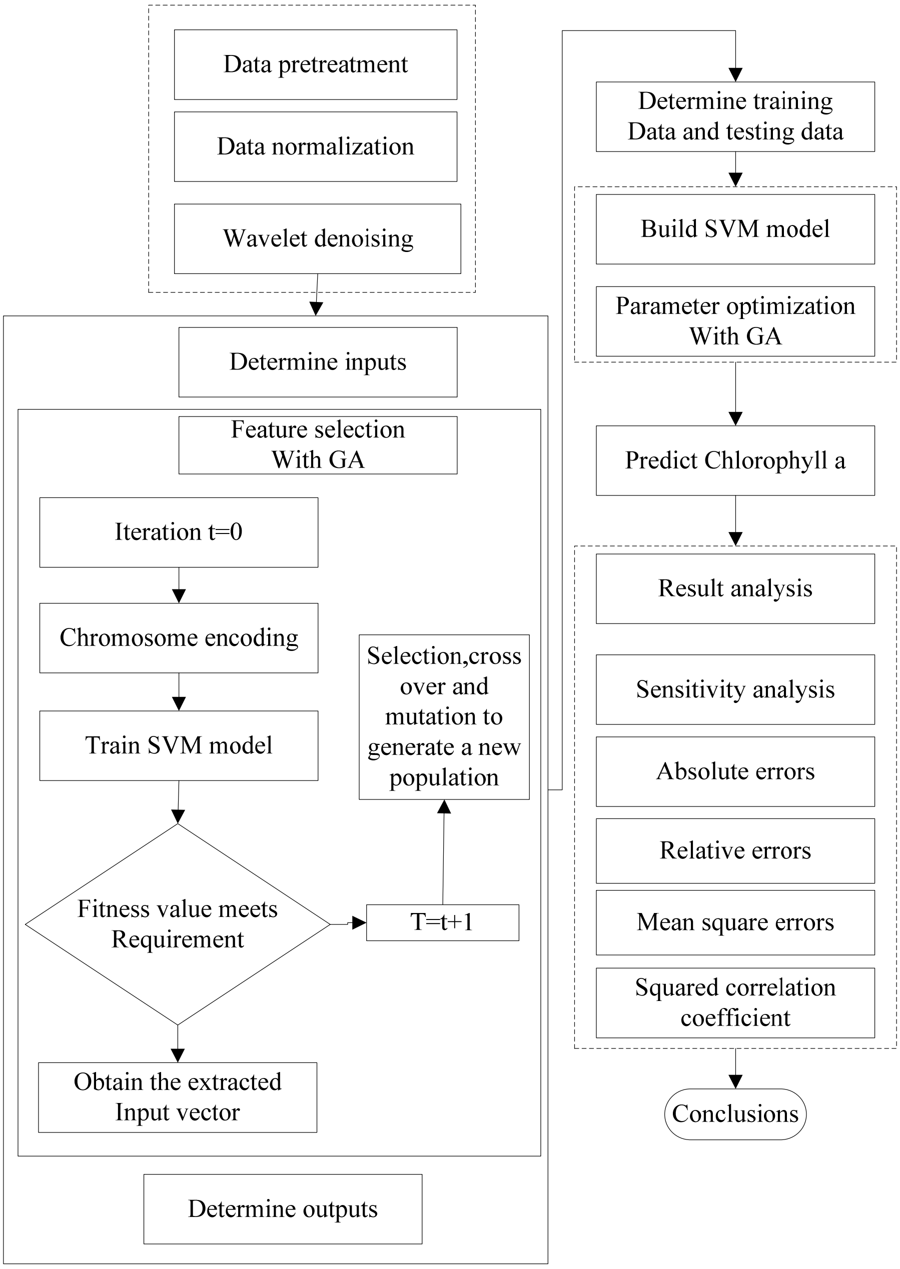

Figure 3: GA-SVM model

5. Conclusions

The South China ore district sample data as an example, genetic algorithm with global searching performance is used to optimize and select kernel parameter g and error penalty factor c in the SVM method, and GA-SVM regression prediction model of metallogenic favorable degree is established. The training data and the testing results show that the GASVM model has very strong applicability in the mineralization favorable degree prediction and it can well simulate the nonlinear relationship between each metallogenic element and the favorable degree of mineralization, with better promotion value.

Compared with the traditional BP neural network algorithm, GA-SVM has more advantages in the prediction of favorable degree of mineralization, with higher accuracy and stronger stability. GA-SVM model is more suitable for small sample regression prediction, which provides a new way for the areas where the ore points are little and the research degree is not deep to find ores, with strong practical significance.

Metallogenic favorability analysis is conductive to understand the process of polymetallic deposit. Effectively making use of existing geological data and scientifically predict the unknown speculation are the key of ore mineral exploration work. With the development of nonlinear mathematical methods in geology application, establish reasonable and effective favorable metallogenic prediction model, to provide technical support for metallogenic prediction, which will become an important development trend in the future ore prospecting.

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