Technical note: The application of an artificial neural network to the prediction of multimetallic deposits

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Synopsis

A back-propagation model, which is typical of the models used in the science of artificial neural networks, was applied to the prediction of gossans from the southeast area of Habei Province in China. A success rate of 100 per cent was achieved.

The results show that the neural-network approach is good, and that it can be used effectively in the prediction of multimetallic deposits.

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Introduction

The technique of artificial neural networks (ANN) is a non-linear technology that began to grow quickly in the mid 1980s. It was initially applied to the fields of pattern recognition, data processing, and automatic control, where it produced satisfactory results.

In 1985, the Parallel Distributed Processing (PDP) Research Group at the Massachusetts Institute of Technology (MIT) in the USA proposed the famous back-propagation (BP) model[1], which has been given very wide application in recent years. This model has a very strong self-organizing and self-learning ability, and it can grasp the nature of things through learning some typical samples. Many problems, such as those of XOR, TC matching, and symmetry discrimination, can be solved by the BP model, which is now one of the models that plays an important role in the study of neural-network theory.

The self-learning algorithm of the BP neural-network model is an iterative procedure. At first, a set of initial weights of the network is given, and then a sample is input to the network and its output is calculated. The difference between the calculated value and the expected value is used to update the weights so that the difference can be reduced. This updating process is repeated until the difference is smaller than a specified error value. After the neural network is 'trained' by the self-learning of sufficient samples, the final weights are taken as its correct interior representation.

Much geological prospecting practice has shown that geological bodies of different types usually have no definite boundaries one from another that can be used to circumscribe or identify geological bodies or geological phenomena. Points sets, composed of points of the same kind of geological bodies or geological phenomena, exist mostly in certain geometrical formations and spatial locations, and are ambiguous and have non-linear characteristics. These are fundamental characteristics of geological structures.

As the traditional mathematical computing methods, known as 'hard computing', originate from classical mathematics and physical science, there are many limitations in the functions, such as 'over precision' in discrimination methods, which means that some information is lost, etc. In recent years, with the development of machine intelligence technology and the continuous addition of new complicated knowledge to computer science, 'soft computing' methods (mainly those of neural networks) have gradually been shown to be able to solve complicated, ambiguous, and non-linear problems, and they have also been applied to geological problems.

In this paper, the BP model, which is a typical ANN model, is used in the identification of two geological bodies, and is compared with the linear discrimination function (LDF) method.

Recognition of gossans

Lui Wenbin *et al.*[2] report on eight chemical elements and give relevant data for about 44 gossans in the southeast area of Habei Province. After certain processing, the content of each element in the gossans was obtained. These data served as the basis of the study reported here.

Establishment of the ANN recognition model

First, 33 samples of gossan were selected randomly as the 'learning' material for the neural network. All the variables (Cu, Pb, Zn, Ag, Mo, W, Bi, Sn) were taken as the input, and the expected outputs of five classes were defined as 0,9 (for the iron mine) and 0,1 (for the copper mine). The hidden layer of the neural network contained eight neurons, and the convergence error of the training set reached 0,001. After learning these samples, the neural network recognized them absolutely correctly, and a complicated corresponding relationship between the chemical elements and the properties of the mines was set up (Table I).

Table I

Compositions of the learning samples

Cu	Pb	Zn	Ag	Mo	W	Bi	Sn	Learning results	Type of mine
0,11	0,08	0,13	0,05	0,17	0,13	0,3	0,3	0,891 333	Iron
0,3	0,11	0,28	0,18	0,2	0,1	0,25	0,3	0,890 732	Iron
1	0,03	0,1	0,1	0,03	0,1	0,25	0,3	0,109 378	Copper
0,4	0,02	0,01	0,03	0,04	0,16	0,25	0,4	0,110 058	Copper
1	0,06	0,3	0,2	0,22	0,15	0,25	0,3	0,109 395	Copper
1	0,66	0,24	0,82	1	0,13	0,25	0,3	0,109 796	Copper
0,42	0,01	0,06	0,08	0,39	0,28	0,25	0,9	0,895 013	Iron
0,75	0,03	0,07	0,05	0,04	0,1	0,25	0,4	0,890 561	Iron
1	0,16	0,21	0,32	1	0,33	0,3	0,8	0,109 660	Copper
1	0,03	0,28	0,36	0,52	0,22	0,3	0,8	0,091 667	Copper
0,16	1	0,3	1	0,13	0,21	1	0,4	0,907 431	Iron
0,07	0,17	1	0,09	0,07	0,1	0,3	0,3	0,097 603	Copper
0,25	1	1	1	0,38	0,25	0,3	0,5	0,091 427	Copper
0,03	0,03	0,06	0,03	0,09	0,1	0,3	0,3	0,890 165	Iron
0,67	0,04	0,07	0,18	0,04	0,11	0,35	0,4	0,101 252	Copper
1	0,03	0,15	0,65	1	1	0,45	1	0,089 895	Copper
1	0,01	0,31	1	0,05	0,1	0,7	0,5	0,089 616	Copper
0,11	0,05	0,09	0,03	0,09	0,1	0,25	0,3	0,903 063	Iron
0,05	0,14	0,32	0,09	0,08	0,1	0,25	0,3	0,898 904	Iron
0,81	0,43	0,53	0,16	0,11	0,11	0,3	0,3	0,089 750	Iron
0,07	1	1	1	0,32	0,11	0,25	0,4	0,089 811	Copper
0,47	0,13	0,44	0,06	0,49	0,47	0,25	0,3	0,106 510	Copper
0,01	0,01	0,14	0,03	0,08	0,1	0,25	0,3	0,890 989	Iron
1	0,1	0,38	0,2	0,44	1	1	1	0,095 098	Copper
1	0,05	0,25	1	0,38	0,25	0,6	1	0,108 756	Copper
0,19	0,07	0,12	0,02	0,08	0,1	0,25	0,3	0,909 597	Iron
0,45	1	1	0,87	0,6	0,13	1	0,5	0,102 062	Copper
0,24	1	1	0,35	0,36	0,13	0,5	1	0,094 279	Copper
0,67	0,09	0,55	0,09	0,36	0,18	0,35	0,3	0,109 716	Copper
0,23	0,01	0,26	0,03	0,04	0,1	0,25	0,3	0,909 893	Iron
0,44	0,07	0,14	0,06	0,17	0,11	0,3	0,3	0,891 020	Iron
1	0,11	0,29	1	0,51	1	0,7	0,4	0,092 126	Copper
0,39	0,01	0,04	0,1	0,05	0,1	0,3	1	0,108 416	Copper

Success rate of recognition

As a test of the performance of the newly established model, 11 samples that had not been used were taken as 'unknown' samples and were input to the neural network, which had grasped the input knowledge necessary for the recognition. These samples were then classified according to how close the actual output was to the expected output. As shown by Table II, the prediction was completely consistent with actuality.

Discussion and conclusion

The BP network turns the input and output problem of a group of samples into a non-linear bettering problem, making use of the gradient-descending algorithm, which is the commonest of the bettering methods. And it extracts the weights, which correspond to the memory problems in learning, through the alternative replacing algorithm, and increases the adjustable parameters of the bettering problem by adding hidden units. Thus, in this way more accurate solutions can be found.

References

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2. LIU WENBIN, *et al. Computational Techniques of Physical and Chemical Prospecting*, vol. 13, no. 2. 1991. pp. 105–109.

Table II

Compositions of the samples for prediction

Cu	Pb	Zn	Ag	Mo	W	Bi	Sn	Results from ANN	Predicted type of mine	Actual type of mine
0,16	0,14	0,12	0,13	0,17	0,11	0,25	0,3	0,819 035	Iron	Iron
1	0,03	0,13	0,03	0,03	0,21	0,25	0,3	0,099 415	Copper	Copper
1	0,05	0,36	0,11	0,13	0,12	0,25	0,4	0,090 649	Copper	Copper
0,02	0,04	0,09	0,03	0,05	0,1	0,25	0,3	0,899 319	Iron	Iron
0,1	0,02	0,11	0,03	0,31	0,1	0,25	0,3	0,820 820	Iron	Iron
0,02	0,01	0,08	0,03	0,2	0,12	0,25	0,3	0,823 136	Iron	Iron
0,21	0,02	0,21	0,03	0,05	0,14	0,25	0,3	0,910 872	Iron	Iron
1	0,03	0,23	0,59	0,53	1	0,5	0,7	0,095 094	Copper	Copper
1	0,1	0,22	0,29	0,77	0,35	0,45	1	0,096 365	Copper	Copper
1	0,05	0,24	0,3	0,69	1	0,25	0,5	0,071 301	Copper	Copper
1	0,17	1	0,99	0,83	0,2	1	0,9	0,226 734	Copper	Copper

If the BP model is regarded as a transformation of input to output, this transformation is highly non-linear. The neural network changes the net into a very complicated function (transformation) that can show the complicated phenomena of the physical world by compounding simple non-linear functions several times.

The LDF method is a traditional method of pattern recognition, but it is one of linear transformation and is not effective in dealing with highly non-linear classification problems.

In the present research, the mathematical nature of the problem calls for a transformation from eight-dimensional space to low-dimensional space (the number of dimensions is less then 8). The resulting classifications show that the neural-network method is better than the LDF method. The former is a transformation from eight-dimensional space to one-dimensional space to achieve the classification (Table I). Its rate of successful prediction is 100 per cent.

Although the LDF method is a transformation from eight-dimensional space to one-dimensional space, it does not achieve correct classification (Table III) and the prediction cannot be carried further.

This inaccuracy is not difficult to understand for the transformation is a highly complicated non-linear one, and a linear classification is not satisfactory.

The neural-network method is much better than linear methods (such as the LDF method) in the fields of classification and prediction owing to its highly non-linear nature. It can be expected that neural networks will play an important future role in geological problems of pattern recognition. ◆

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Table III

The fitted results of the LDF method

Cu	Pb	Zn	Ag	Mo	W	Bi	Sn	+ (>0) or – (<0) of fitted values	Type of mine fitted	Correctness
0,11	0,08	0,13	0,05	0,17	0,13	0,3	0,3	+	Iron	True
0,3	0,11	0,28	0,18	0,2	0,1	0,25	0,3	+	Iron	True
1	0,03	0,1	0,1	0,03	0,1	0,25	0,3	–	Copper	True
0,4	0,02	0,01	0,03	0,04	0,16	0,25	0,4	–	Iron	False
1	0,06	0,3	0,2	0,22	0,15	0,25	0,3	–	Copper	True
1	0,66	0,24	0,82	1	0,13	0,25	0,3	–	Copper	True
0,42	0,01	0,06	0,08	0,39	0,28	0,25	0,9	+	Iron	True
0,75	0,03	0,07	0,05	0,04	0,1	0,25	0,4	+	Copper	False
1	0,16	0,21	0,32	1	0,33	0,3	0,8	–	Copper	True
1	0,03	0,28	0,36	0,52	0,22	0,3	0,8	–	Copper	True
0,16	1	0,3	1	0,13	0,21	1	0,4	+	Iron	True
0,07	0,17	1	0,09	0,07	0,1	0,3	0,3	–	Copper	True
0,25	1	1	1	0,38	0,25	0,3	0,5	–	Copper	True
0,03	0,03	0,06	0,03	0,09	0,1	0,3	0,3	+	Iron	True
0,67	0,04	0,07	0,18	0,04	0,11	0,35	0,4	–	Iron	False
1	0,03	0,15	0,65	1	1	0,45	1	–	Copper	True
1	0,01	0,31	1	0,05	0,1	0,7	0,5	–	Copper	True
0,11	0,05	0,09	0,03	0,09	0,1	0,25	0,3	+	Iron	True
0,05	0,14	0,32	0,09	0,08	0,1	0,25	0,3	+	Iron	True
0,81	0,43	0,53	0,16	0,11	0,11	0,3	0,3	+	Iron	True
0,07	1	1	1	0,32	0,11	0,25	0,4	–	Copper	True
0,47	0,13	0,44	0,06	0,49	0,47	0,25	0,3	–	Iron	False
0,01	0,01	0,14	0,03	0,08	0,1	0,25	0,3	+	Iron	True
1	0,1	0,38	0,2	0,44	1	1	1	–	Copper	True
1	0,05	0,25	1	0,38	0,25	0,6	1	–	Copper	True
0,19	0,07	0,12	0,02	0,08	0,1	0,25	0,3	+	Iron	True
0,45	1	1	0,87	0,6	0,13	1	0,5	–	Copper	True
0,24	1	1	0,35	0,36	0,13	0,5	1	–	Copper	True
0,67	0,09	0,55	0,09	0,36	0,18	0,35	0,3	–	Copper	True
0,23	0,01	0,26	0,03	0,04	0,1	0,25	0,3	+	Iron	True
0,44	0,07	0,14	0,06	0,17	0,11	0,3	0,3	+	Iron	True
1	0,11	0,29	1	0,51	1	0,7	0,4	–	Copper	True
0,39	0,01	0,04	0,1	0,05	0,1	0,3	1	–	Iron	False

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