

# Explicit Simulation of the Tacit Knowledge Based on the Pattern Identification Model

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## Abstract

The pattern identification system summarizes the evaluation value by experts and the empirical value obtained by other methods. At the same time, every sample object has a clear coding relationship with various indicators, and is corresponding to the sample coding. As to the explicit simulation of the tacit knowledge, the author mainly analyzes how to achieve systematic popularization and application of the tacit knowledge. After that, explicit application model of the tacit knowledge based on the support vector machine and the Hopfield network is built, respectively.

Keywords: TACIT KNOWLEDGE, PATTERN IDENTIFICATION HOPFIELD NETWORK

## 1. introduction

Sommeliers use their sense organs to evaluate brewing alcohol quality, guide brewing techniques, storage and blending, design alcohol and develop new products. They should have a thorough understanding of knowledge of different alcohols, including their brewing methods, alcohol terminology and evaluation vocabulary, threshold range of various materials, taste and smell of alcohol (feeling of the tongue), definition of color, flavor and taste of every alcohol, and their respective evaluation methods. Evaluation is a critical technology influencing the brewing level. At present, China has more than 15,600 brewing enterprises with more than 8 million employees, of which nearly 300,000 are sommeliers.

Both sommeliers and professional evaluation teams' judge based on their sense organs and experiences. Their evaluation result might differ since the factors they take into consideration differ. Moreover, their evaluation is an individual behavior. In other words, it is impossible for them to share their eva-

luation standards. To put it more exactly, it is impossible to popularize the current evaluation standards and systems. Considering the problem, this paper employs the pattern identification system to summarize the tacit knowledge of the kind to form a standard tacit knowledge system which can be explicated and popularized through numerical values.

## 2. Explicit simulation of the tacit knowledge based on the support vector machine

Support Vector Machine or SVM was first raised by Vapnik. Similar to multilayer perception network and the radial basis function, it is used for model classification and nonlinear regression. The classifier can be regarded as a linear classifier in the broad sense. Its basic idea is to turn the input space into a high-dimensional characteristic space through the nonlinear transformation, and seek the optimal linear division surface in the new space [1]. The advantage of SVM algorithm lies in its favorable generalization performance. The property is peculiar to SVM. Besides, SVM has the following advantages: 1) Uni-

versality, meaning that it can constitute functions among various functions; 2) Robustness, meaning that it calls for no fine tuning; 3) Effectiveness, meaning that it is always one of the best approaches to solve practical problems; 4) Simple calculation, meaning that the realization of the algorithm calls for a simple optimization technique; and 5) Theoretical maturity, referring to its framework based on VC generalization theories [1].

At the very beginning, SVM is built under the linearly divisible condition. Its basic idea can be explained by the optimal classification plane shown in Figure 6-6, where the solid point and the empty point stands for different data samples, respectively.  $H$  stands for the classification line.  $H_1$  and  $H_2$  stand for the sample straight lines, which are paralleled to the classification line and the nearest to the classification line, respectively. The distance between  $H_1$  and  $H_2$  is called the classification interval. The training sample points on two lines form SVM. Among them, the optimal classification line refers to the correct division of data samples of two kinds. Besides, the classification interval should be ensured to be the maximum. If the optimal classification is applied to the higher space, the optimal classification hyperplane is formed [2].

Below is the description of the optimal classification hyperplane. As to linear and divisible issues, it can be assumed that the set of data samples of two kinds is  $\{(x_i, y_i), i = 1, 2, \dots, n\}, x_i \in R^d, y_i \in \{-1, +1\}$ . The general expression form of the linear discrimination function is:

$$f(x) = \omega \cdot x + b \tag{1}$$

The corresponding classification plane equation is:

$$\omega \cdot x + b = 0 \tag{2}$$

Uniform the discrimination function to ensure all samples to meet the following requirements:

$$|f(x)| \geq 1 \tag{3}$$

Where, when  $f(x) = 1$ , the distance between the sample classification planes on the line is the closest to each other. If (3-42) is to satisfy all sample data on the classification plane, it should also satisfy the following equation:

$$y_i [\omega \cdot x_i + b] - 1 \geq 0 \tag{4}$$

The classification interval is defined as  $d = \frac{2}{\|\omega\|}$ . Obviously, if the classification interval is to reach the maximum, the denominator should be the minimum. [3]  $H_1$  and  $H_2$  are the support vectors, namely the

sample data nearest to the classification plane and are paralleled to the hyperplane of the classification plane,  $H$ . In this way, the question to obtain the optimal classification plane can be turned into an optimization question under restrictions. The minimum of the following function is to be solved:

$$\phi(\omega) = \frac{1}{2} \|\omega\|^2 \tag{5}$$

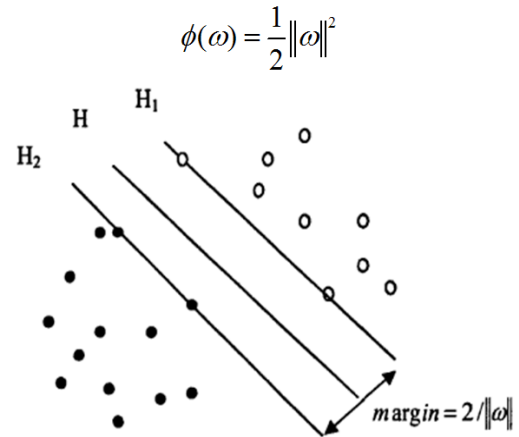


Figure 1. Optimal classification plane sketch

The above introduction is targeted at linear and divisible problems. In terms of the nonlinear problems, the nonlinear transformation should be employed to transform the nonlinear problems in the lower space into the linear problems in the higher space. [4] At the moment, nonlinearity can be transformed to be linear and divisible in the higher space. After that, linear division can be conducted. During the process, kernel function can be used to solve the curse of dimensionality. As to the transformation of the kernel function, the nonlinear division is employed to map the vector,  $x$ , to the higher space through the nonlinear transformation,  $\Phi$ , to design the nonlinear algorithm. [5]

(1)Polynomial kernel function

$$K(x_i, y_i) = [(x_i, y_i) + 1]^d, \tag{6}$$

where  $d$  is a natural number

(2)Radial direction kernel function

$$K(x_i, y_i) = \exp \left[ -\frac{\|x - x_i\|^2}{\delta^2} \right], \delta > 0 \tag{7}$$

(3) Sigmoid kernel function

$$K(x_i, y_i) = \tanh(a(x, x_i) + t) \tag{8}$$

Where,  $a$  and  $t$  are constants; “tanh” is the Sigmoid function.

After a general study of the basic ideas of SVM’s linear divisibility and nonlinear divisibility, the fol-

lowing part introduces several classical training algorithms. [6] The commonly-used training algorithms include Chunking algorithm, decomposition algorithm and SVM algorithm. 1) Chunking algorithm: The algorithm can be used to solve problems during SVM training and storage, which can increase the training speed, but can obtain the optimal results only under the condition that there are few support vectors. 2) Decomposition algorithm: It can be used to solve problems existing in Chunking algorithm, but cannot give full play to its advantages among nonlinear SVM. [8]

The research into SVM classification algorithm has been deepening, and the algorithm of SVM is keeping on improving, such as C-SVM and its varied algorithms,  $\nu$ -SVM, etc. The introduction of the penalty factor,  $C$ , into C-SVM can solve the maximized interval well, and minimize the contradiction bet-

ween the training errors.  $\nu$ -SVM is targeted at the difficulty to choose and improve the parameter,  $C$ , in the algorithm, C-SVM. The parameter,  $\nu$ , in the algorithm,  $\nu$ -SVM, is used not only to control the number and error of the support vector, but also to show the lower bound of the support vector and the upper bound of the interval error. At the same time, lots of experiments have shown that the reduction of  $\nu$  can result in the synchronic reduction of support vectors. [9]

The data used for simulation in this paper come from the UCI database. The database keeps a record of the chemical component analysis value of more than three kinds of wine in the same region. The data contain 178 sample objects. Every sample has 13 indicators, and these indicators are corresponding to the category coding of every sample. Some sample indicators are shown in Table 6-6:

**Table 1. Value of some sample indicators**

Indicators	Category label								
	1	1	1	2	2	2	3	3	3
Alcohol	14.23	13.2	13.16	12.4	12.3	12.6	12.9	12.9	12.8
Malic acid	1.71	1.78	2.36	0.94	1.1	1.36	1.35	2.99	2.31
Ash	2.43	2.14	2.67	1.36	2.28	2.02	2.32	2.4	2.4
Alcalinity of ash	15.6	11.2	18.6	10.6	16	16.8	18	20	24
Magnesium	127	100	101	88	101	100	122	104	98
Total phenols	2.8	2.65	2.8	1.98	2.05	2.02	1.51	1.3	1.15
Flavanoids	3.06	2.76	3.24	0.57	1.09	1.41	1.25	1.22	1.09
Nonflavanoid phenols	0.28	0.26	0.3	0.28	0.63	0.53	0.21	0.24	0.27
Proanthocyanins	2.29	1.28	2.81	0.42	0.41	0.62	0.94	0.83	0.83
Color intensity	5.64	4.38	5.68	1.95	3.27	5.75	4.1	5.4	5.7
Hue	1.04	1.05	1.03	1.05	1.25	0.98	0.76	0.74	0.66
OD280/OD315	3.92	3.4	3.17	1.82	1.67	1.59	1.29	1.42	1.36
Proline	1065	1050	1185	520	680	450	630	530	560

This paper adopts half of samples of every category in the database as training samples, and the other half as test samples. Steps of the model algorithm are shown below:

Step 1: In order to solve the problem of different dimensions of different indexes in samples, all sample objects should be uniformed. Mapminmax of MATLAB is used to solve the problem. The uniformization range is [0,1];

Step 2: Since the penalty function parameter,  $c$ , and the kernel function parameter,  $g$ , in the SVM function are obtained based on experiences, all these training samples can serve as objects and be optimized by the genetic algorithm to seek  $c$  and  $g$  with a better vector basis.

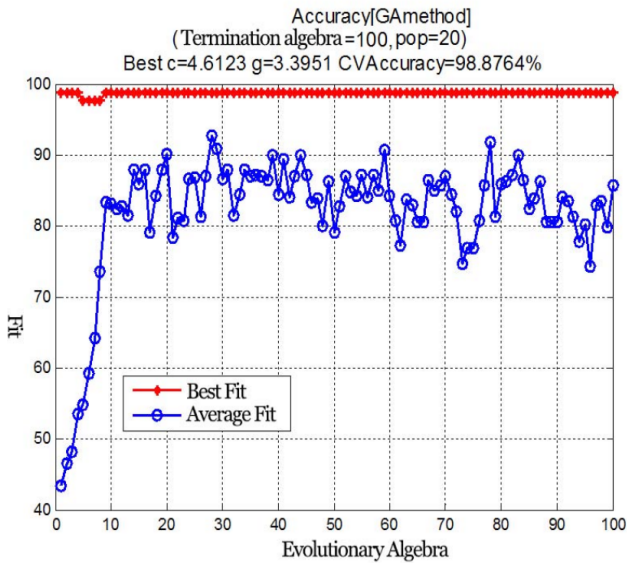
Step 3: The polynomial kernel function is adopted to build the SVM model. Put  $c$  and  $g$  obtained in Step 2 into the SVM model for training.

Step 4: Put the test set into the trained SVM model for simulation, analyze the simulation error and draw the category coding pattern.

Simulation analysis can be conducted through the above steps. The model parameters obtained through the optimization of the genetic algorithm are shown in the following table. The relevant results are shown in Figure 6-7:

**Table 2. Parameter values obtained through the SVM training**

$c$	$g$	Accuracy
4.6123	3.3951	98.8764%



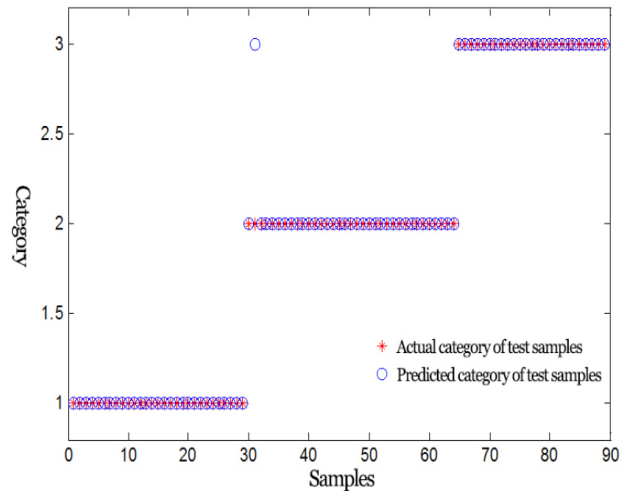
**Figure 2.** Parameter optimization iteration chart of the genetic algorithm

Through the above wine category identification simulation, it can be seen that the parameters after the optimization by the genetic algorithm are  $c=4.6123$  and  $g=3.3951$ . There are 90 samples in the test set in total, of which 89 are correctly predicted. This suggests the accuracy of the test set is as high as 98.8764%. As long as the other wines have the same indicators, the well-trained model can also be applied to the evaluation of the other wines.

The analysis and solution of the SVM model shows that the wine evaluation results obtained by the tacit knowledge of experts can be expressed by the specific SVM model. All in all, the well-trained SVM model can fulfill the role of experts and can popularize and modelize their tacit knowledge.

### 3. Explicit simulation of the tacit knowledge based on the Hopfield network

Earlier in 1983, SONG Huamin from Chinese Academy of Sciences explored the constitution of the scientific research power and the computing method, thinking that scientific research power is made up of six elements, namely basic business skills and scientific research management and organization level of scientific research managers, number and quality of scientific research personnel, scientific research funds, instruments and devices, scientific journals and intelligence, academic accumulation and technical reserve. SONG's study laid a solid foundation for the evaluation of the future scientific research power. The scientific research power of institutions of higher education are made up not only of the scientific research team, the scientific research funds, the scientific research base, the scientific knowledge



**Figure 3.** Simulation results of the test sample model

carrier, the scientific management and the other static elements, but also of the dynamic elements, including the scientific innovation, the information absorption and processing ability, the knowledge application ability, the knowledge accumulation and technical reserve, the self-adjusting ability, the scientific decision-making and so on. ZHU Wenzao thought that the scientific research power is at the core of institutions of higher education, and that the scientific research power of institutions of higher education are made up of the scientific research potential energy and the scientific research kinetic energy. The former refers to the static scientific research elements. They constitute the potential and inherent situation of and the bases and conditions for the scientific research activities carried out in institutions of higher education. The scientific research potential energy includes the scientific research team, the scientific research funds, the scientific research basis, the scientific research management, the depth and breadth of scientific knowledge, etc. The latest research into the evaluation of the scientific research power of institutions of higher education is based on the intelligentized approach, and the self-adaption and self-learning advantages of the neural network. [10]

Hopefield network was first raised by J. J Hopfield, an American physicist, in 1982. [11] It is a fully-connected neural network, introducing new research approaches of the artificial neural network. Hopfield neural network got further improvement and was applied to various fields after further discussion and exploration by some famous scientists, including Gohen, Grossberg and Kohonen. [11] The neural

network is an interconnected neural network used to simulate the memory function of the human cranial nerves. As a feedback network, it regards all nerve cells as equals. Its network model can be shown by a undirected complete graph. Under some conditions, it is random, thus expanding the room for further research. Its evolution process belongs to the nonlinear dynamic system, which can describe the stable balanced state. This suggests that the network system is stable. [12, 13]

Hopfield network is a monolayer feedback nonlinear network. The output of every node is reported to the input of the other nodes. The whole network features continuous self-feedback. Assuming that, there are  $n$  nerve cells, and the network model can be expressed below:

$$\frac{dx_i}{dt} = -\frac{1}{\tau}x_i + \frac{1}{C_i} \sum_j w_{ij}y_j + \theta_j \quad (9)$$

$$y_i = f(x_i) \quad (10)$$

Hopfield network usually adopts the Hebb rules for its learning. The adjustment rule of the weight value is: when the  $i$  and  $j$  nerve cells are simultaneously at an exciting state, the connection between them will be enhanced and the weight value will increase.

$$\Delta w_{ij} = ay_iy_j \quad (11)$$

Assuming that the network has  $p$  orthogonal steady states,  $n$   $V^s = (V_1^s, V_2^s, \dots, V_n^s)$ ,

$s = 1, 2, \dots, p$ , then:

$$w_{ij} = \sum_{s=1}^p V_i^s V_j^s \quad (12)$$

If the newly-increased steady state is  $V_i^{p+1}$ , then:

$$w'_{ij} = w_{ij} + V_i^{p+1} V_j^{p+1} \quad (13)$$

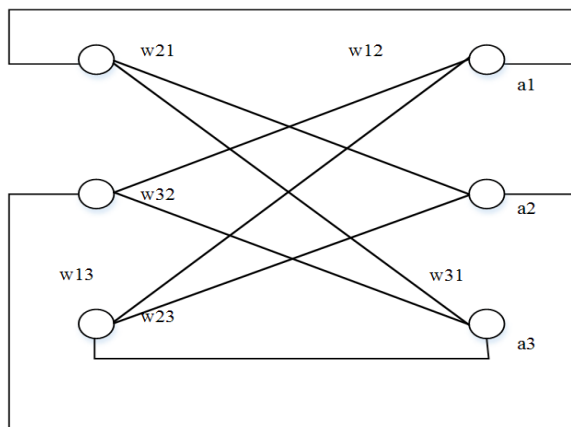


Figure 4. Hopfield neural network structural chart

The discrete Hopfield network is a monolayer feedback network with two-valued input and output. In the DHNN network, every nerve cell has the same function. The output is called state, which is expressed as  $X_i$ . It is mainly used for associative memory. When the initiate state of the network is defined, the network state will change at the direction of decreasing energy according to its working rule, and finally get near or reach the balance point. If the memory pattern required by the network is designed into a balance point and when the network starts from certain initial state relatively close to the memory model, the network state will be updated according to the Hopfield operation rule. At last, the network state will be stabilized to a minimal point of the energy function, namely the state corresponding to the memory model. In this way, the associative memory process from partial information or distorted information to complete information is fulfilled. [12]

The calculation equation of the Hopfield network is shown below:

$$U(t+1) = \sum_{j=1}^n w_{ij}x_j(t) - \theta_j \quad (14)$$

$$x_i(t+1) = \text{sgn}[u_i(t+1)] \quad (15)$$

Where,  $x = [x_1, x_2, \dots, x_n]^T$  stands for the network state vector and the component is the output of  $n$  neural cells, which can only be valued "1" or "-1."  $\theta = [\theta_1, \theta_2, \dots, \theta_n]^T$  is the network's threshold value.  $w = [w_{ij}]_{n \times n}$  is the connection matrix of the network. Its element,  $w_{ij}$ , stands for the connecting right of the  $j$  nerve cell to the  $i$  nerve cell. It is a symmetric matrix, namely  $w_{ij} = w_{ji}$ . When  $w_{ij} = 0$ , the network has no self-feedback; otherwise, it is a self-back network. In the equation,  $\text{sgn}(x)$  is a sign function:

$$\text{sgn}(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (16)$$

The connecting right of the Hopfield network is designed. The main idea of the design method is to make the memorized model sample correspond to the minimum value of the network energy function. Assuming that there are  $m$   $n$ -dimension memory models and the network connection weight value and closed value should be designed. Ensure that the  $m$  models are the  $m$  minimums of the network energy function. The commonly-used method is "exterior product method." Assuming that:

$$U_k = [U_1^k, U_2^k, \dots, U_n^k] \quad (17)$$

Where,  $k = 1, 2, \dots, m, U_i^k \in \{0, 1\} \quad i = 1, 2, \dots, n;$   $m$  stands for the model category number;  $n$  stands for

the number of dimensions of every model type;  $U_k$  stands for the vector expression of the model  $k$ .

Require that  $m$  memory model vectors of the network memory are orthogonal two by two and meet the following equation:

$$(U_i)'(U_j) = \begin{cases} 0 & j \neq i \\ n & j = i \end{cases} \quad (18)$$

The threshold value of various nerve networks is,  $\theta_i = 0$ . The connecting matrix of the network should be calculated through the following equation:

$$W = \sum_{k=1}^m U_k (U_k)' \quad (19)$$

Then, all vectors, such as  $U_k$ , are stable points within the range of  $1 \leq k \leq m$ .

In 198, JJ. Hopfield put forward a continuous Hopfield nerve network (CHNN) based on the discrete HNN. CHNN adopts the analog signals as the input and output of the neural network, and the wor-

king style adopted by various neural cells is paralleled to each other. Though greatly simplifying the biological neuron model, CHNN still shows the major characteristics of the biological neural network system:

- (1)Combination of time and space;
- (2)The neural cells adhere to the I/O conversion and the signals use the Sigmoid function between the input and the output;
- (3)Have the major calculation characteristics, including dynamic condition and nonlinearity;
- (4)Various neural cells are connected by multiple feedbacks.

This paper considers the core competence of institutions of higher education. The critical influencing factors are respectively listed in Table 6-8. The data are an investigation and evaluation of the scientific research power of 20 institutions of higher education, and judged by the peer review. The value of various indicators is shown in Table 6-9:

**Table 3.** Critical indicators of scientific research power of institutions of higher education

Indicators	Serial No.	Indicators	Serial No.
Scale of the scientific research team	X1	Scientific research management system	X7
Scale of the scientific research base	X2	Information treatment capability	X8
Scientific research information and data	X3	Learning and knowledge accumulation	X9
Scientific research input	X4	Scientific research innovation	X10
Knowledge summarization	X5	Scientific decision-making and judgment	X11
Scientific research adjustment	X6		

Adopt the average of various indicators of the above grade samples as the grade threshold. In other words, the average value of various indicators of objects of various grades is the ideal grade

evaluation and division standard. Therefore, the standard threshold value of indicators of various grades obtained through calculation is shown in the following Table 6-10.

**Table 4. Peer review of 20 institutions of higher education according to the above indicators**

Serial No.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	Grade
1	98	92	86	95	90	97	93	96	92	95	94	1
2	92	96	94	88	95	91	89	97	93	90	99	1
3	73	87	82	65	89	74	86	80	94	81	82	2
4	78	71	76	91	82	89	80	78	63	76	84	2
5	87	96	93	97	92	95	90	88	96	98	94	1
6	68	72	64	66	69	61	65	70	75	63	67	3
7	61	64	62	57	67	68	72	64	63	69	62	3
8	38	43	51	62	48	57	53	46	49	50	54	4
9	53	46	47	58	55	36	39	48	52	58	47	4
10	94	97	91	96	87	93	98	92	86	94	95	1
11	24	37	45	31	18	29	33	13	22	38	30	5
12	84	80	71	78	73	83	74	67	82	88	75	2
13	44	58	55	45	62	54	46	59	55	45	43	4
14	35	23	16	27	38	24	29	28	38	21	26	5
15	16	44	32	38	26	35	20	37	34	33	39	5
16	65	67	68	62	61	58	63	69	64	62	66	3
17	58	65	62	67	71	69	64	65	70	74	65	3
18	73	84	95	78	84	86	76	83	89	75	87	2
19	33	28	35	20	26	44	39	26	30	44	24	5
20	94	89	96	94	91	99	95	87	93	88	88	1

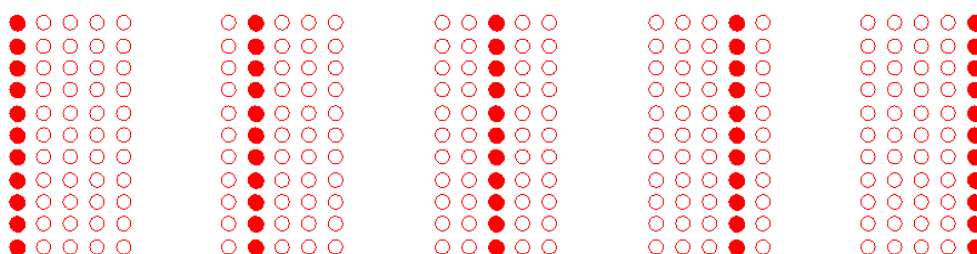
**Table 5. Standard value of various indicators of various grades**

Grade	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
1	93	94	92	94	91	95	93	92	92	93	84
2	77	78	71	78	83	83	79	77	82	80	82
3	63	67	64	63	67	64	66	67	68	67	65
4	45	49	51	55	55	49	46	51	52	51	48
5	27	33	32	29	27	33	30	26	31	34	29

Based on the above value obtained through the peer review, the Hopfield network established is evaluated. The steps of the model algorithm are listed below:

Step 1: Since “-1” and “1” are two kinds of information input to the Hopfield network, it is necessary

to code the standard grade samples. There are 11 indicators in total, every of which has five grades. Solid points can meet indicators of various grades, but empty points cannot. The ideal coding of various grades are shown in Figure 6-10 below:



**Figure 5. Ideal coding structure of various grades**

Step 2: Build the Hopfield network model. Adopt all the above standard grade coding as the network input information and to train the Hopfield network.

The kernel pseudo-code program based on MATLAB is shown below:

T=[Grade 1, Grade 2, Grade 3, Grade 4, Grade 5];

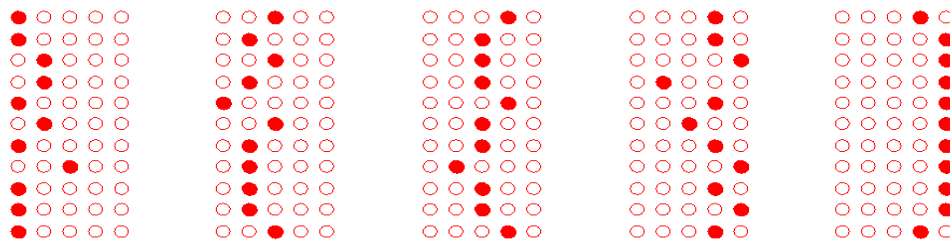
net=newhop (T).

Step 3: Put the test data set into the trained Hopfield network model for simulation. The number of

iterations is 20. The distribution of various indicators of various test samples and grades is shown in Table 6-11 and Figure 6-11.

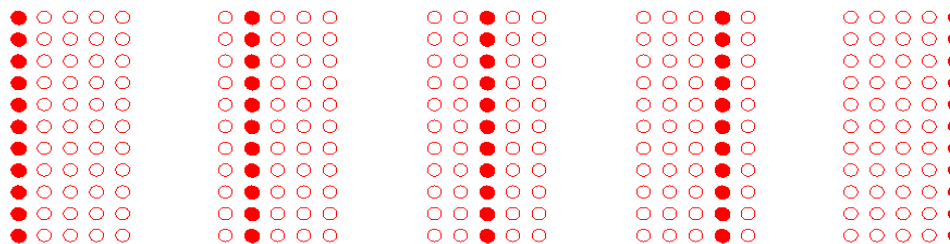
**Table 6.** Distribution of grades of various indicators of the test samples

Serial No.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
1	96	92	85	89	93	87	94	76	98	94	97
2	70	88	75	82	96	79	89	80	84	85	83
3	60	75	68	67	57	74	76	83	69	75	64
4	55	59	59	41	81	58	73	57	48	43	55
5	20	38	38	42	25	24	37	40	36	46	35



**Figure 6.** Grade distribution chart of various indicators of the test sample

The standard distribution and convergence results through the above steps are shown in Figure 6-12: of the grades of the samples to be tested obtained



**Figure 7.** Hopfield network model simulation results of the test samples

From the above Hopfield network model simulation results, it can be seen that the value of various indicators obtained through peer review can serve as the input information of the Hopfield network model to establish the Hopfield network evaluation model. In this way, experts' tacit knowledge can be effectively summarized and expressed, and achieve explicit application and promotion.

**4. Conclusions**

Explication process of the tacit knowledge of different aspects is provided through various models. Based on the grade distribution and evaluation of certain model type, the center of clustering is adopted as the division standard for the potential indicators of experts' tacit knowledge, which is of vital guiding significance. At the same time, the experts' tacit knowledge is expressed through the modeled

approach. Cases about sommeliers' taste of red wine are analyzed, and expressed by the SVM algorithm. Results show that: The well-trained SVM model can replace the peer review and can popularize and even modelize experts' tacit knowledge. At last, Hopfield network model is employed to simulate results. It can be seen that the value of various indicators obtained through the peer review are adopted as the input information of the Hopfield network model, based on which the Hopfield network evaluation model is built. The evaluation model can effectively summarize and express experts' tacit knowledge, and even conduct explicit application and promotion of it.

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