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Research on Life Cycle Evaluation of Industrial Technology Innovation Alliance Based on Support Vector Machine SVM

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Abstract: *Different stages of alliance life cycle have different effects on the decision-making and development of enterprises, so the division of alliance life cycle plays an important role in the survival and development of member enterprises. This paper puts forward the index of dividing alliance life cycle, and constructs the evaluation system of support vector machine. BP neural network and support vector machine are used to establish the evaluation model, and the accuracy of the model is compared to verify the effectiveness of the alliance life cycle division index. The evaluation model based on support vector machine has high accuracy and applicability, which provides an efficient method for alliance life cycle division.*

Keywords: *Support Vector Machine SVM, Industrial Technology Innovation Alliance, Life Cycle*

1. Introduction

Life cycle theory believes that organizations are like living organisms, following the law of life from birth, growth, maturity to decay. Yin Wang (2016) summarized previous research findings and found that the life cycle of an organization or product in an economic environment is mainly divided into four stages: development, growth, maturity, and decline. Zhong Haiou (2013) and Wu Ting et al. (2010) divided the life cycle of industry-university-research alliances into the formation period, the growth period, the maturity period, and the decline and extinction period. Ni Yuan (2015) divides the alliance development cycle into four phases: networking phase, development phase, stable phase and transformation phase. Feng Lichao (2018) believes that the life cycle of the University Association for Science and Technology Alliance is the start-up period, the growth period, the maturity period and the transformation period. Therefore, this article draws on the above scholars' viewpoints and divides the life cycle of the industrial technology innovation alliance into the formation period, the development period, the maturity period and the recession period.

2. Evaluation Index System

This paper uses the "Measurement Scale of Alliance Development Stages" developed by Ni Yuan et al. to identify the stage of alliance development. The scale has 13 items, and the evaluation index system is shown in the table. Since the evolution of the life cycle of the alliance presents nonlinear characteristics, this research uses the machine nonlinear algorithm support vector machine to process data and judge the stage of the alliance.

3. Construction of SVM Model

3.1. The Concept of Support Vector Machines

Support Vector Machines (SVM, Support Vector Machines) is a widely used machine learning method. In 1995, Vapnik proposed a support vector machine based on the statistical learning theory VC dimension theory and the structural risk minimization principle (SRM, Structural Risk Minimization).

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The mechanism feature of the support vector machine is to map the data to the appropriate dimension and find an optimal hyperplane that meets the classification requirements, so that the hyperplane can maximize the blank area on both sides of the hyperplane while ensuring the classification accuracy. At the same time, the classification performance of the support vector machine is affected by many factors, among which the following two factors are more critical: (1) the error penalty parameter c; (2) the kernel function form and its parameters. The error penalty parameter c is a compromise between the proportion of misclassified samples and the complexity of the algorithm, that is, adjusting the confidence range of the learning machine and the empirical risk ratio in the determined feature subspace, which affects the promotion ability of the learning machine. The selection of the kernel function also has a direct impact on the pros and cons of classification performance. The selection of parameters is more complicated, and improper selection of parameters may lead to overfitting and thus affect the classification performance of the classifier.

As an efficient general machine learning method, the principle and mechanism of support vector machines are simple. This method has a concise mathematical form and intuitive geometric interpretation, which can better solve the problems of small samples and nonlinearity, and can overcome the defects of "dimensionality disaster" and local minima. Because this method is based on the principle of minimizing structural risks, it also has good generalization capabilities.

3.2. The basic principle of SVM

SVM is a linear classifier in the parameter space. When the training data is linearly inseparable, it can be expanded into a non-linear classifier through a kernel function. Transform the input space into a high-dimensional space, find the optimal classification surface in this new space, and use different kernel functions to implement different classifiers. In this paper, the radial basis kernel function is selected, and it is a non-linear classifier.

The non-linear support vector machine transforms the input variable x into a high-dimensional space through a non-linear transformation, and the optimal classification surface is obtained through the transformed space, and the inner product operation is performed in the high-dimensional space. Only the kernel function satisfies the Mercer condition and the input variable Mapping to high-dimensional Hilbert space through nonlinear mapping, if defined:

$$K(x,y)=\Phi(x)\cdot\Phi(y) \tag{1}$$

The objective function of "Maximum Interval" is:

$$W(\alpha)=\sum_{j=1}^{l}\alpha_i-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}y_iy_j\alpha_i\alpha_jK(x_i\cdot x_j) \tag{2}$$

The corresponding classification function is:

$$f(x)=\mathrm{sgn}\left[w\cdot\Phi(x)+b\right]=\mathrm{sgn}\left[\sum_{i=1}^{l}y_i\alpha_iK(x_i\cdot x)+b\right] \tag{3}$$

$$y_i\left\{\left[w\cdot\Phi(x_i)+b\right]\right\}\geq 1-\xi_i \qquad \xi_i\geq 0, i=1,\ldots,l \tag{4}$$

Therefore, the optimal problem is transformed into:

$$\begin{cases} Min \quad \Phi(w)=\frac{1}{2}(w\cdot w)+C\sum_{i=1}^{l}\xi_i \\ s.t. \quad y_i\left((w\cdot\Phi(x_i))+b\right)\geq 1-\xi_i \end{cases} \tag{5}$$

$$\begin{cases} Max \quad L(\alpha)=\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}y_iy_j\alpha_i\alpha_jK(x_i,x_j) \\ s.t. \qquad 0\leq\alpha_i\leq C,\sum_{i=1}^{l}y_i\alpha_i=0, i=1,\ldots,l \end{cases} \tag{6}$$

The form of the support vector machine depends on the form of the kernel function it selects. In the existing research, the most commonly used kernel functions are as follows:

$$K(x,y)=\left[s(x,y)+c\right]^{d} \tag{7}$$

$$K\left(x_i \cdot x_j\right)=Exp\left(-\frac{\left|x_i-x_j\right|^2}{\sigma^2}\right) \tag{8}$$

$$K(x,y)=tanh\left[s(x \cdot y)+c\right] \tag{9}$$

3.3. SVM classifier application process

Support vector machine is based on statistical theory, and is different from traditional statistical learning theory. It is mainly for small sample situations, and the optimal solution is based on limited sample information, rather than the optimal when the number of samples tends to infinity solution. This algorithm includes various processes, such as initialization, selection of kernel function, selection of penalty parameters, etc., in order to find a hyperplane that can be used for linear division as a solution to the problem. The support vector machine algorithm has better approximation performance.

(1) Preprocess the original data, and use the processed data as the input value of the classifier.

(2) Set the kernel function, penalty parameter c and gamma and other parameters. This article chooses the radial basis function (RBF, Radial Basis Function)

(3) After the risk test, use the training samples to train the classifier optimized by the penalty parameters c and gamma until the error requirements are met, and the construction of the industry-university-research alliance knowledge sharing performance evaluation model is completed.

(4) Input the processed data into the trained classifier, and reverse normalize the output results to obtain the predicted value of the knowledge sharing performance of the industry-university-research alliance

4. Empirical Research on Life Cycle Evaluation of Industrial Technology Innovation Alliance Based on Support Vector Machine

4.1. Data collection

The industrial technology innovation alliance life cycle evaluation indicator system includes 13 projects, of which 12 input indicators are core enterprise development stage, core enterprise scale, alliance network scale, alliance specialization, alliance communication mechanism, number of well-known brands, alliance technology Maturity, alliance innovation ability, social resource flow, partner flow, external support, and alliance entry barriers; output index 1 and the question is "Which stage do you think your alliance is in the life cycle". The questionnaire uses a five-level Likert scale, and the scores from low to high are 0.1, 0.3, 0.5, 0.7, and 0.9 respectively. To evaluate the life cycle of an industrial technology innovation alliance, it is necessary to quantify the life cycle of the alliance. The output value is between 0 and 100, 60-70 is the formation period, 70-80 is the decline period, 80-90 is the growth period, and 90-100 Maturity.

The sample quantity and quality determine the reliability and effectiveness of network prediction. In order to avoid poor sample quality, low model prediction accuracy, and improve model prediction effects, we selected managers, middle-level cadres and employees with years of work experience from alliance member companies as the survey subjects. The survey respondents have in-depth understanding of the production, learning, and research and development (R&D) of their respective units, and they send out questionnaires in the form of WeChat, visits, emails, etc., and use the advantages of the college's MBA class to issue questionnaires in the class. A total of 500 questionnaires were distributed, and after excluding invalid questionnaires, 340 valid questionnaires were obtained.

4.2 Life Cycle Assessment Results of Industrial Technology Innovation Alliance

This study uses 12 industrial technology innovation alliance life cycle evaluation indicators as input

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items and life development stage evaluation results as output items to construct a support vector machine SVM prediction model for alliance life cycle evaluation. First of all, in MATLAB (R2018b), the SVM classifier is used to test 280 sets of test samples and the performance of alliance life cycle evaluation. In the support vector and calculation process, it is also necessary to write and test the calculation process in MATLAB software. This article uses experimental trial and error method to set the parameter value range. The penalty parameter is: c=[0,400], and the kernel width is σ=[0.01,10], and then input the collected original sample data into the program, with the alliance life cycle evaluation index as the input value, and the alliance life cycle development stage as the output value. During the sample data training process, the parameters need to be adjusted according to the actual situation, and the training is repeated to the optimum. Finally, the results are compared with the results obtained by the traditional BP neural network. After repeated experiments, the final SVM algorithm parameters used in this article are shown in Table 1. The number of nodes in the input layer, hidden layer and output layer of the BP neural network are 12, 25, and 1, respectively.

The influence of SVM parameter selection on the SVM prediction result is as follows:

a) Penalty parameter c: In the case of linear inseparability, the degree of penalty for classification errors. If the c value is too large, it will cause overfitting; if the c value is too small, the classifier performance will be poor.

b) Gamma: Select RBF as the parameter that comes with the kernel function. If the gamma value is too large, it will also cause overfitting; if the gamma value is too small, the classifier will underfit.

4.3. Comparison of Support Vector Machine Svm and Bp Neural Network Prediction

In order to determine the effectiveness of the support vector machine SVM, the prediction result of the support vector machine SVM is compared with the prediction result of the traditional BP neural network. Two indicators of relative error (E_{MR}) and relative error variance ($RMSE$) are used to evaluate the performance of the prediction model; the robustness of the model is measured by the coefficient of determination. The smaller the relative error in formula (2), the more accurate the prediction result. The closer the coefficient of determination in formula (4) is to 1, the higher the correlation degree, and the closer the prediction result is to the target value.

In order to verify the efficiency of the support vector machine SVM, the performance of the model is evaluated from two aspects: the average relative error (E_{MR}) and the root mean square error ($RMSE$), and the coefficient of determination (R^2) is introduced to test the robustness of the support vector machine classifier model.

$$E_{MR} = \left[\sum_{i=1}^{m} \frac{\left| y_i - f(x_i) \right|}{y_i} \Big/ m \right] \times 100\% \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(y_i - f(x_i) \right)^2} \tag{11}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} \left(f(x_i) - y_i \right)^2}{\sum_{i=1}^{N} \left(f(x_i) \right)^2} \right) \tag{12}$$

(1) Error comparison

Through the SVM prediction model and the BP neural network prediction model, the predicted value of the alliance life cycle stage is obtained, and the actual value is compared, as shown in Figure 1. It can be seen from Figure 1: Compared with the predicted value, there is a certain gap between the predicted value of the BP neural network after training and the predicted value of the support vector machine, and the predicted value of the SVM model is closer to the target value, indicating that the SVM model has higher accuracy degree.

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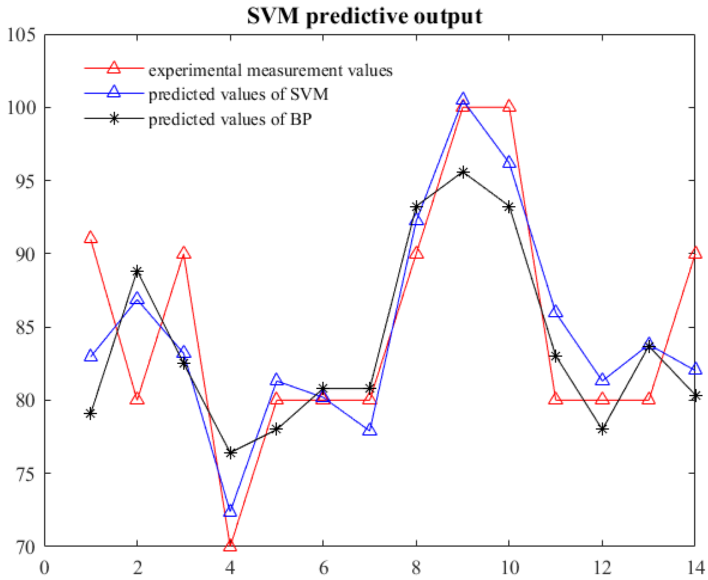

Figure 1: Comparison of predicted values of BP neural network and SVM

It can be seen from Figure 2 that the maximum absolute error of the prediction value of the alliance life cycle development stage evaluation results of the SVM model is 6.8759, and the minimum is -7.9779. The maximum absolute error of the BP neural network is 8.8398, and the minimum is -10.9168, indicating that it is compared with the BP neural network. The forecast model of the alliance life cycle development stage of the network, and the forecast model of the alliance life cycle development stage of the SVM is more stable.

Figure 2: Comparison of prediction absolute error between BP neural network and SVM

It can be seen from Figure 3 that the relative errors of the SVM prediction model and the BP neural network prediction model are both below 13%. However, the maximum relative error of the SVM prediction model is 8.86%, and the maximum relative error of the BP neural network prediction model is 12.13%, and the relative error of the SVM prediction model is better than the BP neural network prediction model as a whole. The data proves that the prediction model based on SVM-based alliance life cycle development stage evaluation results has higher prediction accuracy.

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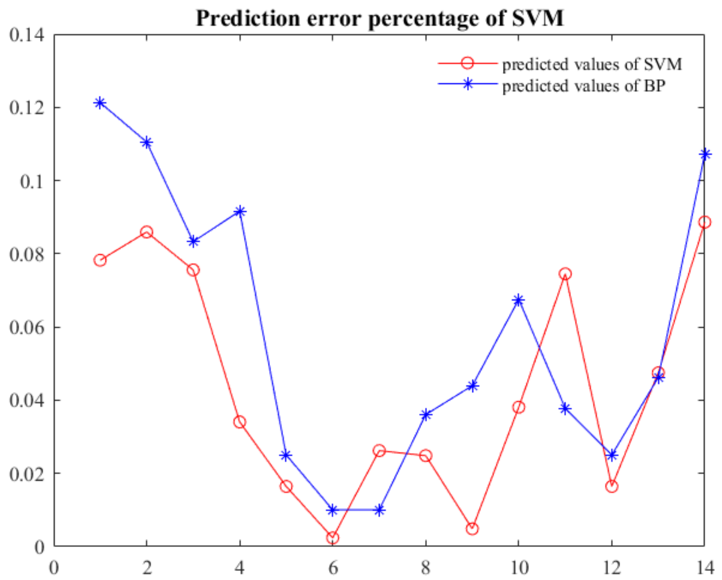

Figure 3: Comparison of prediction relative error between BP neural network and SVM

It can be seen from Table 1 that the average relative error of the predicted value of the SVM model is 4.38%, and the root mean square error is 4.55. The average relative error of the predicted value of the BP neural network prediction model is 5.83%, and the root mean square error is 5.95. The data proves the SVM The model is more stable than the BP neural network prediction performance.

Table 1: Comparison of prediction performance between BP neural network and SVM

Prediction model	Maximum relative error/%	Minimum relative error/%	Average relative error/%	Rmse
Bp	12.13	1.01	5.83	5.95
Svm	8.86	0.24	4.38	4.55

(2) Fitting performance

Figures 4, 5, and 6 respectively show the robustness of 340 sets of overall samples, 280 sets of training samples, and 60 sets of test samples of the support vector machine SVM prediction model in the development stage of the alliance life cycle. Figure7 shows the robustness of the BP neural network test samples. Awesome. It is shown in Table2.

Table 2: Robustness comparison between BP neural network and SVM

Models	Sample	R2
SVM	Training samples	0.999311
SVM	All samples	0.998770
SVM	Test samples	0.997159
BP	Test samples	0.995148

The closer the coefficient of determination is to 1, the better the fitting effect. The results show that the value of the test sample of the SVM model is closer to 1 than the value of the BP neural network. It can be seen that the generalization ability of the SVM model is stronger, which proves that the SVM model has a great Good robustness, so the prediction performance of the SVM model is better than that of the BP neural network.

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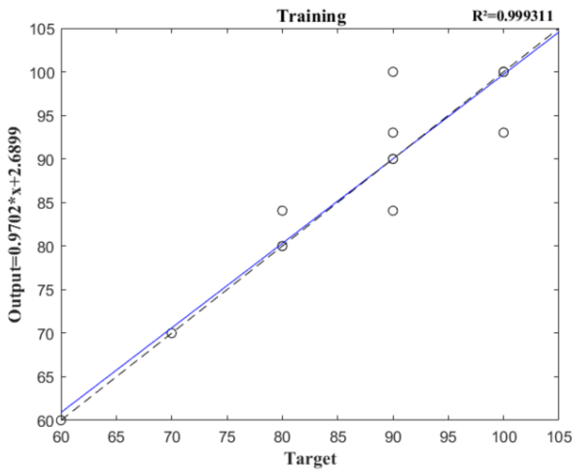

Figure 4: SVM training data fitting performance chart

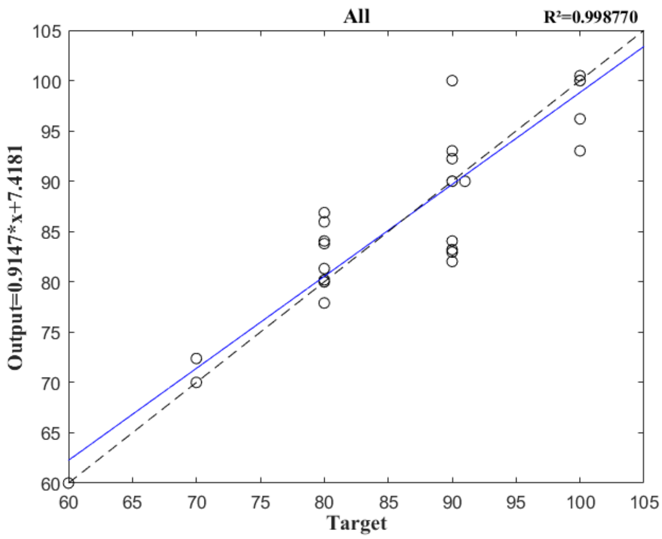

Figure 5: All data fitting performance of SVM

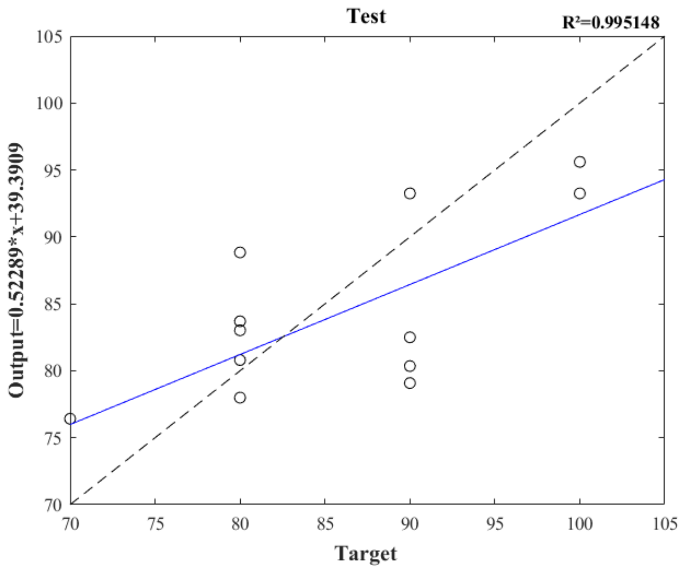

Fig. 6: Prediction performance of SVM of all samples

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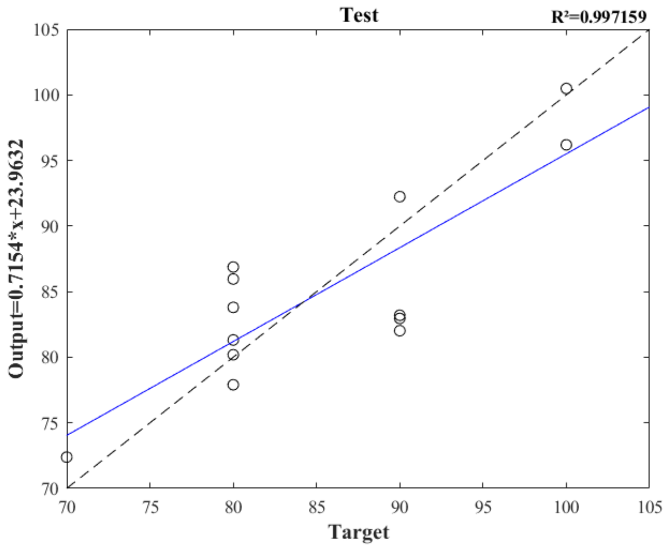

Figure 7: Performance chart of BP neural network test data fitting

In order to compare the classification performance of the SVM classification model, the SVM is compared with another BP algorithm used in this paper. The results are shown in Table 1 and Table 2. In terms of relative error and root mean square error, the error of SVM is smaller than that of BP, and SVM has an absolute advantage in classification accuracy. From the results of data fitting, it can be seen that the model fitting effect of SVM algorithm is obviously better than that of using SVM. The BP algorithm model has significantly improved the classification effect. In this paper, SVM classifier and BP neural network are used to solve the problem of alliance life cycle prediction. Classification accuracy is an important indicator to evaluate the classification performance of the model. The experimental results show that the classification accuracy of SVM is higher than that of BP neural network, so SVM classification is used. The method is better than BP neural network. Comprehensive calculation results show that it is feasible and accurate to use support vector machine SVM to predict the life cycle of alliances.

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