Revista Argentina de Clínica Psicológica
2021, Vol. XXX, N°2, 938-947
DOI: 10.24205/03276716.2020.4101

Prediction of Financial Economic Time Series based on Group Intelligence Algorithm based on Machine Learning

ZhaoHui Fu[a], ZhiJuan Wang[a]

Abstract
The prediction of financial economic time series can help investors avoid risks and obtain higher returns by forecasting the future price according to the historical transaction data of financial transaction varieties (such as stocks). However, the financial economic time series is a chaotic time series which is extremely complex, nonlinear, non-stationary and high noise related. Therefore, the prediction of financial economic time series is considered to be the most difficult topic in the study of modern time series. This paper mainly studies the prediction of financial economic time series based on Group intelligence algorithm based on machine learning, The advantages of this prediction can only improve the quality of clustering, reduce the calculation amount, improve the speed of operation, and make the regression analysis and prediction of financial time series more effective. This paper mainly uses machine learning method, support vector regression and SVR algorithm to study the financial economic time series prediction based on group intelligence algorithm based on machine learning. Support vector regression (SVR) is widely used in financial time series prediction, and it shows stronger prediction ability than traditional artificial neural network. This is mainly because SVR is a machine learning algorithm based on statistical learning theory, which has good nonlinear approximation, fast convergence, global optimal solution and strong generalization ability. The results show that the algorithm combines the prediction algorithm of multiple SVR models in five research samples, selects multiple SVR models in different training data sub group training, and uses reasonable weight combination to predict the results. The diversity of models is used to reduce the overall prediction error. The weights of each model are dynamically adjusted according to the latest prediction accuracy, so it has the adaptability and can deal with the problems caused by the non-stationary. The algorithm of mixing multiple SVR models can significantly improve the accuracy and generalization ability of financial time series prediction.

Key words: Machine Learning, Group Intelligence Algorithm, Financial Economic Time Series Prediction, Svr Algorithm

Introduction

With the development of social economy, finance has become the core of modern economy. Financing is an important part of national competitiveness, and the essence of financing lies in the circulation of value. With the development of financial information, its liquidity is becoming stronger and stronger. Like the "blood" of the whole society and economy, it has penetrated into all aspects. The effective development of modern financial industry plays an important role in promoting the overall economic development. Therefore, it is of great practical significance to study the essential characteristics of financial market and analyze and grasp the potential development laws, which will help to maintain the sustainable development of financial market and provide effective decision support for financial management and investment activities.

Financial market is a complex market affected by social, economic, political, investor psychology and financial activities. Financial data is a

Corresponding Author. College of Business, Inner Mongolia University of Finance and Economics, Hohhot 010000, Inner Mongolia Autonomous Region, China. Email: Fzh102937@163.com.
College of Business, Inner Mongolia University of Finance and Economics, Hohhot 010000, Inner Mongolia Autonomous Region, China. Email: 15548140410@163.com.

comprehensive expression of the complexity of financial market. In a large number of financial data, especially financial time series, financial market analysis is often called financial time series analysis. From the perspective of time series analysis, financial market analysis is often called financial time series analysis, The main contents include: basic analysis, technical analysis, mathematical statistics analysis and data mining technology, among which basic analysis and technical analysis are relatively simple, they are usually used to analyze the financial time series of securities market. They can analyze the surface information of historical data, but they cannot dig the hidden attributes and rules of these data. The mathematical statistical model can analyze the more complex statistical characteristics and rules in the historical data, but they cannot effectively adapt to the increasing financial data caused by financial information.

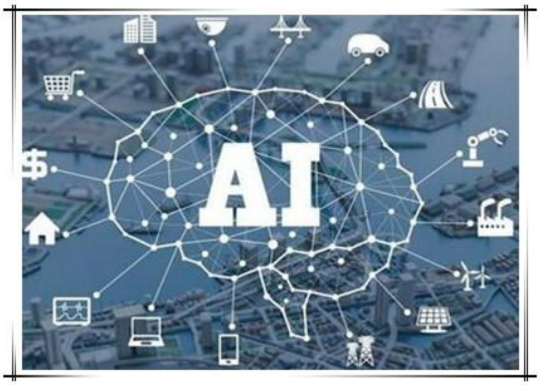
The development of information technology has a great impact on the financial economy. The application of information technology in financial management decision-making, concrete operation and financial information affect the development of enterprises and products and other processes. Financial information promotes the sustainable development and in-depth analysis of economic and financial resources, and can adapt to the needs of financial modernization and promote the sustainable and effective development of social economy. Mullainathan S thinks machines are increasingly doing "intelligent" things. Face recognition algorithm uses a large photo data set to estimate a function, which predicts the presence of face y from pixel X. Machine learning not only provides new tools, but also solves a different problem. Specifically, machine learning is around prediction, while many economic applications focus on parameter estimation. Therefore, it is necessary to find the relevant tasks to apply machine learning to economics. Machine learning algorithms are now technically easy to use: you can download easy packages in R or python. This also increases the risk of naive application of algorithm or distorted output, which makes them more easily used conceptually, but there is no specific data at present [1]. Singh A believes that high throughput phenotype opens up a new prospect for non-destructive field phenotype, semi-autonomous or manual platform equipped with single sensor or multiple sensors collects space and time data, thus generating a large amount of data for analysis and storage. HTP data generated by these platforms is large, various and fast, which has become a "big data" problem. These big data generated by these near real-time platforms must be archived and retrieved efficiently for analysis. Complex data collection, storage and processing become ubiquitous, and new areas of applications are emerging. ML algorithm is a very promising method, it can analyze data faster, more efficiently and better. It is multidisciplinary in itself. It draws inspiration and concepts from probability theory, statistics, decision theory, optimization and visualization, but lacks necessary experimental data [2]. Obermeyer Z believes that a centralized literature review of machine learning and data mining methods supports intrusion detection, and a brief tutorial description of each ml/dm method is required. According to the number of references or the relevance of new methods, identification, reading and summary represent each method. Because data is very important in ml/dm method, it is necessary to introduce some famous network data sets and complexity of ml/dm algorithm for ml/dm. The challenges faced by using ml/dm algorithm in network security are introduced, and some suggestions are put forward on when to use the given method, but the content of numerical analysis is missing [3]. Buczak A believes that deep reinforcement learning has been successful in the game, but 2.5D combat games will be a challenging task to deal with, because in visual appearance, such as height or depth of character blur. In addition, the actions in such games usually involve specific sequential action sequence, which makes the network design very difficult. The computer creates an open game environment similar to the gym, and proposes an a3c+ network to learn RL agent. The model includes a circular information network, which uses the game related information features with the circular layer to observe the combined skills in the combat. In the experiment, LF2 under different environments is considered, and the application of the proposed model in 2.5D combat game learning is proved successfully, but it can be used for reference but some of the discussions are not accurate [4].

In this paper, the innovation of this paper is to study the prediction of financial economic time series based on group intelligence algorithm based on machine learning, such as machine learning method, support vector regression and SVR algorithm. Combined with the idea of information fusion in financial market, the performance of this algorithm in other types of non-stationary financial time series is investigated [5].

2. Machine Learning Method

2.1 Machine Learning

Machine learning is an interdisciplinary subject, involving probability theory, statistics, approximation theory, convex analysis, computational complexity theory and other fields. How to improve the performance of the system through the intelligent calculation of computer and the application of experience, the corresponding algorithm model is generated by experience, and the process of establishing algorithm model is actually the process of machine automatic learning [6-7]. Machine learning is an interdisciplinary subject, involving probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory and other disciplines. It focuses on how computers simulate or realize human learning behaviors, so as to acquire new knowledge or skills, reorganize the existing knowledge structure, and constantly improve their own performance. The generation of learning algorithm includes the process of simulating human thinking, demonstrating incomplete information, constructing and discovering new things, and processing current big data [8]. At present, machine learning algorithms are mainly divided into the following categories: supervised learning algorithm, unsupervised learning algorithm and semi supervised learning algorithm; Classifications are input variables and discrete categories [9]. Unsupervised learning algorithm means that we don't know which results will appear in the output in advance. For example, we can extract a specific structure from the data by clustering, while there are no labels or only the same labels in unsupervised learning [10]. Semi supervised learning is a learning method that combines supervised learning and unsupervised learning. In the process of machine learning, there are both



marked data and empty data. Semi supervised learning can improve the efficiency and accuracy of learning, and has been paid more and more attention by machine learning researchers, as shown in Figure 1:

Figure 1. **machine learning**

（**http://alturl.com/dkays**）

2.2 Machine Learning Theory

(1) Structural risk minimization

The principle of structural risk minimization is also a theory in statistical learning, which is similar to the trade-off of deviation and variance, and can also be used to guide the selection of models, assuming that a machine function f (a, b) is identified by its variable parameter a [11]. Suppose the machine is deterministic: for a given input and a selected B, the output f (a, b) is always the same. Training machine is the process of selecting B in some way by using the given input a [12]. For example, a neural network with fixed structure is a learning machine, and B corresponds to its weight and threshold. The expected test error of a machine obtained by training is as follows:

$$H(b) = \int \frac{1}{2}|x - f(a,b)|dP(x,y) \quad (1)$$

H (b) is called expected risk. In this paper, we call it actual risk to emphasize that it is the value we are interested in. We hope that the trained machine will have the minimum practical risk, and the prediction error of the machine will be as small as possible no matter in the training samples or in the future samples, that is to minimize the generalization error [13-14]. But because P (x, y) is usually unknown, the actual risk cannot be calculated directly. The principle of empirical risk minimization is to minimize the error of the machine in the training samples [15]. Empirical risk (also known as training error) r (a) is defined as the average error rate measured on the training set, as shown in the formula：

$$R(a) = \frac{1}{2d}\sum_{i=1}^{t}|y_i - f(a,b)| \quad (2)$$

In order to notice that there is no probability distribution in the above formula, it is not necessary to know or assume the distribution of samples in advance. After is selected, the empirical risk can be calculated according to the above formula [16]. However, for the limited training mode, the actual risk of the machine with the lowest empirical risk is not necessarily the smallest, and it cannot well summarize the future samples. Fortunately, there is also a connection between the empirical risk and the actual risk, for the selected machine η（ 0 ≤ η In the following formula, 1 -- η The probability of the model is true:

$$H(b) \le R(a) + \sqrt{\frac{c\left(\log\frac{2d}{c}+1\right)-\log\frac{\eta}{4}}{d}} \quad (3)$$

（2）Support vector regression

Support vector machine was originally used to solve classification problems. By introducing a new loss function, carrier vector machine can be used in regression problems. This variable is generally called SVR support vector increment [17]. The basic idea of vector regression support (SVR) is to nonlinearly map data to high-dimensional function space, and solve the linear regression problem in this space, which means to construct a super horizontal plane as close to the data points as possible to make the super horizontal plane as flat as possible, the training test should be (R, t), the input variable R is m-dimensional vector, and the output variable t; R is a continuous value and N is the number of samples. The purpose of the regression task is to evaluate the regression function:

$t = f(r) = w \cdot \varphi(r) + b$ （4）

Where w ∈ R, Φ(x) the original nonlinear solvable problem can be transformed into a linear problem in a high-dimensional space by assigning nonlinear input variables to a high-dimensional space R. according to the basic idea of support vector regression, the regression function should minimize the following risks. The general formula is as follows:

$R = \frac{B}{n}\sum_{i=1}^{n} H\,(x, y) + \frac{1}{2}\left\|e\right\|^2$ （5）

Among them, the first empirical risk (training error), X is the output of regression function, and the predicted result y is the actual output; the second term refers to structural risk (used to prevent learning), the smaller e, the smoother the hyperplane. B is a correction coefficient used to represent the balance between empirical risk and structural risk. The higher the value of B, the more attention is paid to the empirical risk, and vice versa, the more attention is paid to structural risk [18-19].

(3) Decision tree algorithm

Decision making is a common learning method in machine learning. It has achieved good results in classification, prediction and rule extraction. The tree structure consists of three parts: root node, branch node and leaf node, and root node is also decision node. It is usually the attribute of sample to be classified in records, and branches are different values of root node [20]. The leading node is the possible classification result. C4.5 algorithm uses the measurement of information gain rate, which is an improvement of information entropy. Under the condition of given information sharing cost, C4.5 algorithm can partially affect the number of attribute values, thus improving the general ID3 decision tree calculation method, and taking training data set s as its information entropy calculation formula as shown in the following figure:

$Entrpy(H) = -\sum_{i=1}^{m} s\, log_2 \quad s$ （6）

Where s is the frequency of category items with m category items in all samples, suppose that a is used to divide the data into H, a is discrete, K takes different values, h is divided into k subnumbers, attribute a is divided into the information entropy of H, gain (h, a) is divided into data sets, and the information gain of H is equal to the entropy of H minus the entropy of the sample after a divides h, as follows:

$Entropy(H) = -\sum_{i=1}^{m} s\, log_2\, s$ （7）

C4.5 algorithm introduces the splitting information of attributes to adjust the expression of information gain, as shown in the following formula:

$splitE(A) = -\sum_{i=1}^{k} \frac{R_i}{R} log_2 \frac{|R_i|}{|R|}$ （8）

In continuous attribute data, C4.5 algorithm processes the data according to the order of attribute value increasing. The center of each pair of adjacent values is regarded as a possible point. According to the information entropy of left and right clauses, the minimum information entropy of the data set is calculated as the best sub point of the attribute, and the minimum information entropy is used as the information entropy of the attribute partition data set:

$GainRatio(V) = \frac{Gain(V)}{SplitE(V)}$ (9)

2.3 Svr Algorithm

The main limitation of SVM and SVR is the high amount of computation in training, testing and stage. Therefore, when the problem is large, it is usually divided into several smaller problems. The algorithm first selects a data subset as the calculation set, and uses the general optimization algorithm to optimize the subset. Other data are replaced by the newly selected data, and the newly selected data must violate the KKT condition. It can be proved that the value of loss function is decreasing. After the sequence minimization algorithm is proposed, the extreme decomposition method is adopted, and each working set contains only two points. The biggest advantage of this algorithm is that it can be optimized iteratively, as shown in Figure 2:

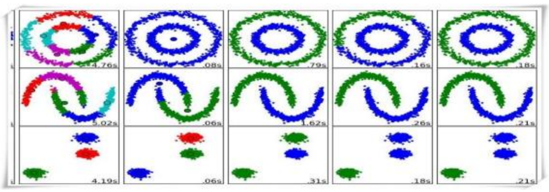


Figure 2. SVR algorithm (http://alturl.com/k2uxe)

The generalization ability (prediction accuracy) of SVR depends on the selection of SVR parameters and core function parameters to a large extent. The selection method of parameters must be adjusted according to the application field to reflect the distribution of input variables in training data.

2.4 Cross Validation Method

Cross validation can train different models and compare the expected prediction errors of each model, so as to select the optimal combination of parameters. If there is enough data, then some data can be reserved as verification set to evaluate the prediction errors of the model. But data is usually scarce, so this approach is not feasible. To solve this problem, k-fold cross validation uses some data for training model and the rest for test model. The method divides the data into N parts with the same size. One part is kept in turn (assuming the nth part, k = 1,2, n is retained, and the M Training Model (marked as f (m) is combined with the parameters on the remaining N — 1 data, and then the prediction error of the model on the nth data is calculated (recorded as HN (m)), Finally, the mean value of k-times prediction error is taken as the estimation of prediction error of these models, as shown in the formula:

$$CV(f,m) = \frac{1}{n}\sum_{i=1}^{n} H_n\,(m) \quad (10)$$

The function CV (F, m) gives the curve of the test error changing with the parameter combination M. the parameter combination (denoted as m) which makes the test error minimum can be found on the curve. The final model can be obtained by training with the parameter combination m on all data. The prediction error (HN (m)) of the model is usually measured by root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m-f)^2}{n}} \quad (11)$$

N is the number of test data; f is the predicted output and M is the actual output. In the calculation process, particle swarm optimization algorithm is used to evaluate the applicability of each particle: it is determined by the combination of parameters corresponding to the particles and the 50 times cross validation method for the training data. The formula for the particle suitability is as follows:

$$Fitness = 1 - FAMD \quad (12)$$

The classification of SVM includes linear separable and linear indivisible problems. For linear separable samples, the vertical bisector of the two boundary lines can be directly used for the linear separable samples. The hyperplane is expressed as follows:

$$a + hy = 0 \quad (13)$$

The parameter is the intercept, which determines the position of the hyperplane. If it is generalized linear separable, the objective function needs to add a penalty parameter to adjust the error partition rate:

$$min\, s\,(a) = min(\frac{||a||^2}{2}) + b\sum_{i=1}^{m}\varepsilon) \quad (14)$$

Where, B is the penalty parameter. The higher the total allowable error score, the lower the overall classification accuracy. The maximum hyperplane is completely determined by the support vector. At this time, the support vectors all fall on the boundary, so as to determine the hyperplane, as shown in the formula:

$$A = \sum_{i=1}^{m} b_i x_i h_i \quad (15)$$

3. Related Experiments of Financial and Economic Time Series Prediction

3.1 Intelligent Model for Prediction and Calculation of Financial and Economic Time Series

At present, the research of financial time series prediction model is mostly from the overall perspective of model structure, based on the core algorithm. For example, pca-ga-svm model is based on SVM algorithm, using PCA and GA for data reduction and dynamic updating of model parameters, to improve the stability and predictability of SVM algorithm. On the basis of RBF algorithm, principal component analysis is used to simplify the input indexes, determine the main evaluation indexes, and solve the problem of insufficient input samples. The feature extraction process of historical data is taken as the key step of the prediction model design, and the prediction model is established according to the ideas of historical input, feature extraction and local nonparametric similarity prediction. In the modeling process of financial time series forecasting intelligent model, it is necessary to establish a basic forecasting model, so a data-driven nonparametric model can be considered. Nonparametric model is one of the commonly used prediction models at present, mainly including nonparametric regression and neural network. Nonparametric regression is very suitable for the modeling of nonlinear dynamic system analysis because it is derived from chaos theory and recognition pattern. KNN is one of the nonparametric regression methods with mature theory, simple and intuitive algorithm principle.

3.2 Data Sets

The stock price index is the average price that indicates the change of stock market. It covers a wide range and can objectively reflect the stock market. Therefore, this study uses the stock price index to carry on the experiment. The five global stock price indexes used in the experiment are listed. The symbols in the table are the symbols used in this paper, as shown in Table 1:

Table 1. **Stock price index used in the experiment**

Index	code	time span
Hong Kong Hang Seng Index	HSI	1986 to 2012
Korea composite index	KS11	1997 to 2012
Nikkei 225 index	NK	1984 to 2011
Dow Jones index	DJI	1928 to 2011
Australian common stock index	AORD	1984 to 2012

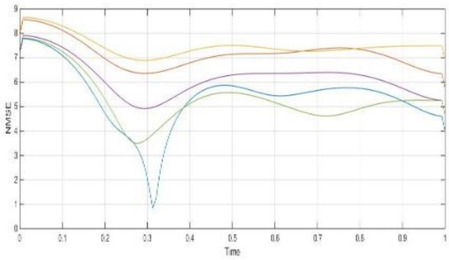
The data will come from Yahoo Finance website. The original data includes the opening price, closing price, transaction price, highest price, lowest price and trading volume of each trading day. The closing price is used in the experiment. The historical period of the data set contains many important economic events, so the corresponding time series is inactive, which is enough to verify the performance of the algorithm proposed in this paper, in this paper, multiple SVR models are mixed on non-stationary financial time series. The first mock exam is the first mock exam. The experimental results show that the prediction error of the mixed model NMS is 40% to 60% lower than that of the single model, and the WDS is about 20% to 50%. The prediction error of the single model is close to 1, so the predictability of the hybrid model is obviously better than that of the random model, as shown in Table 2:

Table 2. **Experimental results under standard algorithm configuration**

Code	model	NMSE	WDS	RMSE
AORD	single mix	0.8845	0.5498	0.2387
DJI	single mix	0.6785	0.7623	0.4455
HSI	single mix	0.9543	0.2398	0.6621
KS11	single mix	0.6534	0.7654	0.9987
NK	single mix	0,3765	0.6523	0.7776

3.3 Prediction Error of the Model Changes with Time

In order to analyze the change of model prediction error with time, the prediction result is divided into 50 time periods, and the NMS of each time period is calculated. The prediction error of hybrid model and SVR model in hybrid model is compared. The black line represents the hybrid model, and the 225-day length index is used. It requires a standard algorithm configuration. In any period, the prediction error of the hybrid model is generally lower than that of other models. Therefore, the hybrid model can effectively deal with the inactive financial time series and maintain high prediction accuracy when the market structure



changes, as shown in Figure 3:

Figure 3. **Comparison of prediction error between hybrid model and other models**

3.4 selection of Technical Index of Securities

The premise of forecasting the stock market is the selection of technical indexes. A large number of studies show that the basic volatility of the securities market has regularity. According to the technical analysis theory of securities forecasting, the future trend of the securities market index is closely related to the current securities market. Technical index method is an important branch of securities technical analysis. In the past, most of the securities forecasts were based on the closing index of the securities market. However, experiments show that it is not very effective to directly use these samples for forecasting. The reason is that the data used is too single and the package is too small, the amount of information contained is insufficient. Therefore, a large number of historical information of technical indicators is very important for the prediction of stock market index time series. Through the analysis of the historical information, we can find its inherent change law to carry out index prediction. However, there are a large number of securities technical indicators, and the prediction ability and accuracy of each indicator are different, so it is impossible to consider them equally. Therefore, based on data mining technology, through the research of related literature, combined with the actual situation of the securities market and a large number of experiments, 34 technical indicators commonly used in the securities market are selected as the input characteristics of the model.

4. Financial and Economic Time Series Prediction

4.1 Shenzhen Stock Market Closing Index Forecast

In order to analyze the relationship between the predicted value and the real value of PCA, 2D and R algorithms, each algorithm is adjusted to the optimal output. In order to obtain the optimal prediction accuracy of the Shenzhen stock market closing index, the calculation value of the performance index predicted by the above algorithms. The P values of the three algorithms are greater than 0.05, indicating that there is no significant difference between the predicted value and the real value, indicating that each feature extraction algorithm is reasonable and effective+ The results show that all the performance indexes of PCA algorithm show a certain prediction advantage, and its SCC is 0.9823, R is 0.9911, higher than other algorithms, MSE is 282.03, RMSE is 16.794, MAE is 13.339, lower than other algorithms. This shows that compared with 2D algorithm, PCA algorithm can produce lower prediction error and has better prediction performance. At the same time, each performance index of 2D algorithm is better than PCA algorithm, which shows that the feature extraction algorithm based on second-order tensor is better than vector-based algorithm, which can better retain the original information of data and make the extracted features more representative, as shown in Table 3:

Table 3. **Shenzhen stock index prediction performance index**

Algorithm	PCA	2D
F value	0.05	0.23
P value	0.876	0.564
MSE	250.34	345.32
SCC	0.234	0.345
RMSE	14.232	12,276
R	0.786	0.897

The chart in Table 3 shows the closing index prediction chart when the optimal prediction accuracy of Shenzhen stock index is obtained respectively based on PCA algorithm and PCA algorithm. It can be seen that for Shenzhen stock index, the real value of PCA algorithm is the best, and the effect is the best. Although the prediction trend of 2D algorithm is close to PCA algorithm, the curve change is not smooth enough. The error of R algorithm is the most obvious and the fluctuation is the largest, as shown in Figure 4:

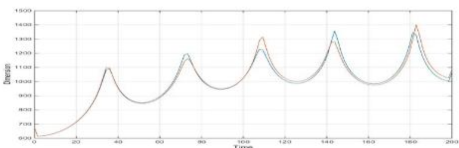


Figure 4. **Shenzhen stock market closing index forecast**

It can be seen from the figure that when the optimal prediction accuracy is obtained, the comparison between the number of features extracted by these three algorithms and the total operation time consumed by the system (including feature extraction and neural network prediction time) is compared. When the optimal prediction accuracy is obtained, the feature dimension extracted by PCA algorithm is the least, which shows that the feature extracted by PCA algorithm can keep the original data information to the maximum extent. The feature extraction and dimension reduction of two dimensions of data can greatly reduce the feature dimension and reduce redundant information.

4.2 Generalization Capability of Model

Generalization ability is an important indicator of the model, and there is no problem of over learning. For the prediction model, generalization ability can be regarded as the ultimate goal of model optimization, because we are concerned about the performance of the model in future data, namely, its expected prediction error, In the case of only one given dataset, as shown in Table 4:

Table 4. **Training error and test error of single mixed model**

Stock index code	training error		test error	
	NMSE	WDS	NMSE	WDS
AORD	0.6752	0.5789	0.7921	0.4365
DJI	0.6678	0.5321	0.7698	0.3337
HSI	0.6430	0.4889	0.8754	0.4001
KS11	0.6031	0.5222	0.7999	0.3990
NK	0.6999	0.4338	0.8111	0.3881

It can be seen from table 4 that the training error and test error of other stock indexes are similar to those of Australian common stock index. First, we investigate the performance of the two models in WDS index. Compared with the first mock exam, the prediction error of the hybrid model is not improved. On the first mock exam or on the test set, the average prediction error of the hybrid model may be larger than the average value of a single model (such as AORD, DJI, HSI three indexes). However, the first mock exam is roughly the same, so the two models are not different from the single model in terms of WDS index. On the NMSE index, the hybrid model has obvious improvement. Compared with the first mock exam, the training error and the test error of the hybrid model are significantly reduced. Moreover, compared with the first mock exam model, the training error of the hybrid model is less than the test error. Therefore, for the first mock exam, the generalization ability of the hybrid model is significantly higher than that of the NMSE model.

4.3 Input Vector Dimension

When introducing the selection of input vector and output variable of SVR, the dimension m of input vector is discussed. In this section, the algorithm configuration is similar to the standard algorithm configuration, but different dimension m of input vector and delay Dare selected for experiment. The model is trained with training data, and tested on test data. The prediction error on test data is calculated, as shown in Table 5:

Table 5. **Influence of input vector dimension m and delay D on prediction error of hybrid model**

m	d	NMSE	WDS	RMSE
1	1	0.8865	0.5321	0.3662
1	2	0.7432	0.4888	0.3777
1	3	0.6762	0.5432	0.3455
1	4	0.6676	0.4388	0.3499
1	5	0.6789	0.3455	0.3001

The first mock exam is the first mock exam and the other is the comparison between the prediction results of the single model and the mixed model. The comparison is made between the experimental results of the single model and the mixed model. The input vector dimension M = 5 and the delay d = 2 are used to retest the single model and the mixed model. The relationship between the predicted values of the three algorithms and the corresponding real values is analyzed. This paper uses Dow Jones stock market technical index data to carry on the experiment. Table 3-4 shows the performance index calculation values of each algorithm when the Dow Jones closing index achieves the optimal accuracy. The P values of the three algorithms are all greater than 0.05, indicating that there is no significant difference between the predicted value and the real value, which indicates that the second-order feature extraction algorithm is better than the vector-based algorithm, as shown in Figure 5:

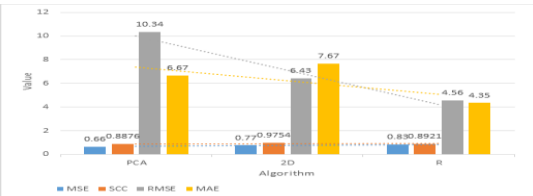


Figure 5. **Characteristics of virtual reality technology**

At the same time, the corresponding feature dimension and the total operation time consumed by the system are compared when the three algorithms obtain the optimal prediction accuracy.

When the optimal prediction accuracy is obtained, the feature dimension extracted by PCA algorithm is the least, which is 38 dimensions, which indicates that the features extracted by PCA algorithm can better retain the main information of sample data, the prediction accuracy can be obtained by using fewer features. From the overall operation time, PCA algorithm has the least time and can achieve higher prediction accuracy in a relatively short time. But the time of feature extraction is 0.4432 seconds, which is larger than that of 2D algorithm. The reason is that it performs the second feature extraction based on 2D algorithm, which consumes time. The less prediction time is because the dimension of feature is reduced step by step after PCA algorithm performs the second feature extraction, which reduces the computation amount of RBF neural network and shortens the operation time, The overall prediction time is shortened by combining feature extraction and neural network prediction time as shown in Figure 6:

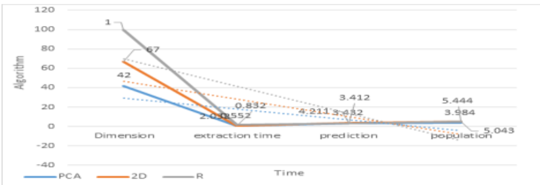


Figure 6. **Comparison of characteristic dimension and operation time of Dow Jones index**

The covariance matrix is constructed for both the row and column dimensions of the original second-order tensor samples. Its dimension is far lower than that of the original data, and its computational complexity is far less than that of PCA algorithm, which transforms the data into vectors and results in a large amount of computation of the covariance matrix, so the feature extraction time is small. Because the feature dimension extracted by PCA and 2D algorithm is less, the data operation of RBF neural network is reduced, so the prediction time is shorter than PCA algorithm. The swarm intelligence algorithm is shown in Figure 7:

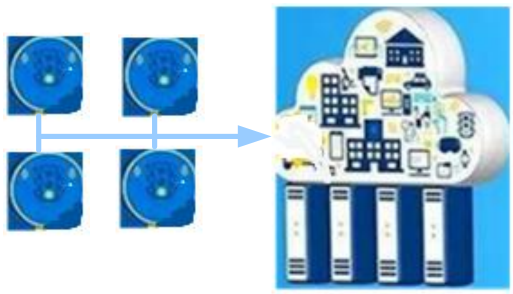


Figure 7. **Swarm intelligence algorithm （http://alturl.com/ue9kf）**

In the analysis of the stock market forecasting model in group intelligence algorithm, the technical analysis index is an indispensable tool for reasonable prediction. The specific values of technical indicators and the internal relations among the indicators provide theoretical basis for the prediction of price or trend in the later period. Therefore, it can be seen that the time series prediction results of securities market index are closely related to technical indicators. In most cases, it is more effective to predict the timing of buying or selling by combining multiple technical indicators than simply using the closing price. However, in practice, the information represented by the technical indicators of the securities market often give different hints at different times, sometimes even contradictory situations. At this time, investors should not only have a thorough understanding of technical indicators, but also experience of old ways, so as to correctly judge the future trend of stock price. But there are a lot of technical indicators in the securities market, different technical indicators reflect different characteristics of the market. Therefore, it is not to use more indicators to predict the better, but to explore a model to improve the accuracy of index research and judgment.

5. Conclusion

In this paper, machine learning method, support vector regression and SVR algorithm are used to study the prediction of financial and economic time series based on swarm intelligence algorithm of machine learning, In the follow-up research, different parameters can be used to train SVR model, different SVR core functions can be used, different learning algorithms (such as artificial neural network) can be used to train the model, or different sampling methods can be used to select training data subset. Through the analysis of the experimental results, it is found that the hybrid model algorithm proposed in this paper may still have large errors in a certain period of time. In the follow-up research, we can analyze the causes of this phenomenon and explore the improvement methods. When the time delay is 1, the prediction results of the hybrid model algorithm and the single SVR model are almost the same, and even the prediction error may be larger. This problem can be analyzed in the follow-up study. Forecasting financial time series is a basic element of any investment activity. The concept of investment itself is to invest existing resources to achieve future profits. This concept is based on the concept of future forecasting. Therefore, forecasting financial time series is also the basis of investment activities of the whole investment industry (including all organized stock exchanges and other securities trading systems), only fully grasp and predict its development trend, can better create the future.

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