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Prediction of bank telephone marketing results based on improved whale algorithms optimizing S_Kohonen network

Chun Yan [a], Meixuan Li [a], Wei Liu [b,*]

[a] College of Mathematics and System Sciences, Shandong University of Science and Technology, Qingdao 266590, China
[b] College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China

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ABSTRACT

Time deposit has the characteristics of strong stability and low cost. It is a stable source of funds for banks. In this paper, S_Kohonen network is used to predict the success rate of fixed deposit in bank telephone marketing. Firstly, the output layer is added after the competition layer of unsupervised Kohonen network, which makes Kohonen network become S_Kohonen network with supervised learning. Because the improved S_Kohonen network is similar to other feedforward neural networks, each adjacent layer is connected by weights, and the initial weights are random, which easily leads to the unstable output of the network, and still has the disadvantage of relatively low prediction accuracy. Therefore, an improved whale optimization algorithm (IWOA) is proposed to optimize the weights between the input layer and the competition layer of S_Kohonen network. In this paper, the inertia weight of whale optimization algorithm is introduced into random factor on the basis of non-linear decline, and then the random search pattern of Levy flight is introduced into whale algorithm. Finally, the empirical results show that the improved S_Kohonen network can more intuitively represent the classification results of the network, and the classification accuracy of S_Kohonen network optimized by IWOA is significantly higher than that of S_Kohonen network optimized by GA , WOA and LWOA algorithm.

1. Introduction

Whether a bank can operate normally or not, the most basic factor is sufficient deposits. Time deposit has the characteristics of strong stability and low cost, so it is a stable source of funds for banks [1]. Time deposit has always been the main source of funds for banks, and the marketing of time deposit has become the daily work of bankers. Therefore, how to improve the success rate of marketing has become an important problem that banks need to solve urgently.

Marketing is a powerful means to improve business. With the development of society and the progress of communication, marketing activities have gradually moved from offline to online, and the communication between people has become more convenient. Telemarketing is a low-cost marketing mode, which is widely welcomed by banks. Communication over the telephone can not only make it easier for customers to understand the relevant information of products, but also the level of business. But through the way of aimless and wide-spread network, although it can broaden the crowd of customers, it also causes a lot of waste of resources, and even causes harassment to some users. Therefore, we need to establish effective ways to find target groups and improve the marketing success rate. Evaluate available information and customer indicators through data mining, focusing on maximizing customer lifetime value so that we can build longer and closer tasks with business needs [2]. Selecting potential buyers from a large number of customers is considered a NP-hard problem [3].

In recent years, many scholars have applied data mining technology to improve telemarketing in order to find target groups and improve the success rate of telemarketing. Mei Ruiting uses Lasso and Support Vector Machine (SVM) to predict whether customers order time deposits. Finally, the results show that the combined forecasting method of Lasso and support vector machine is superior to the three forecasting methods of SVM, neural network and Lasso-neural network [1]. Xuan Z Y used three models of CART, Adaboost and Naive Bayes to predict the marketing success rate. By comparing the Kappa and AUC values of each model, it was found that Naive Bayes showed the best results [4]. Sérgio Moro proposes an artificial intelligence decision support system, which uses data mining method to select bank telemarketing customers. The final result shows that 79% of successful sales can only contact half of the customers, and the previous practice of connecting banks with all customers has increased by 29% [5]. Moro uses data-based sensitivity analysis

* Corresponding author.
E-mail address: liuwei_doctor@yeah.net (W. Liu).

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to extract feature correlation, and conducts expert evaluation on feature decomposition of telephone marketing contacts. The final result proves that reassessment of inbound telephone marketing leads to a significant improvement in target performance [6].

Kohonen network is a self-organizing competitive neural network. It is an unsupervised learning network, which can cluster automatically according to environmental characteristics. The network adjusts the weights of the network through self-organizing feature mapping, so that the network converges to a manifestation. In recent years, Kohonen network has been applied in various fields. Santos uses principal component analysis and Kohonen self-organizing map to evaluate macronutrient content in soft drinks [7]. Skowron uses Kohonen network to classify the electrical faults of induction motors [8]. Li Accurate Recognition of Coal–Rock Interface Using Kohonen and LMD Replacement Entropy [9]. Through the application of Kohonen network in many fields and the excellent performance of Kohonen network, this paper proposes to use Kohonen network to predict the success rate of telephone marketing. Firstly, Kohonen unsupervised network is transformed into S_Kohonen network with supervised learning, which not only retains the advantages of Kohonen network, but also more intuitively shows the predicted results. Considering the random initial weights between the input layer and the competition layer of S_Kohonen network, it is easy to cause the unstable output of the network and the unsatisfactory convergence effect of the network, this paper proposes a whale optimization algorithm (WOA) to optimize the initial weights of S_Kohonen network.

Traditional network prediction structure usually has some shortcomings, such as complex parameter setting, long training time, and easy to be disturbed by outlier sample points, which affect the prediction accuracy of the model. Therefore, it is very important to select the optimal network parameters in the prediction model. If these parameters are not selected properly, the network convergence speed will be slow and the prediction accuracy will be affected. In order to solve this problem, group intelligence algorithm is widely used to optimize the network structure, find the optimal weight and threshold of the prediction model, and thus determine the optimal prediction structure [10]. Whale optimization algorithm has the advantages of less required control parameters and good computational stability, etc., which has attracted the attention of technicians in various fields. Moreover, scholars have applied it to the engineering field, and obtained better computational results, such as reservoir optimization and turbine optimization [11]. Due to the excellent performance of whale algorithm, many scholars have used whale algorithm in network optimization [12–14].

WOA algorithm is a relatively new intelligent algorithm, which has the advantages of simple mediation parameters and fast operation. Scholars often use whale algorithm to optimize the weights of networks. Li uses the WOA algorithm to optimize the limit learning machine to evaluate the aging degree of IGBT module [15]. Bui applies whale algorithm to feature selection and parameter adjustment of adaptive neuro-fuzzy inference system (ANFIS) [16]. Lin Chunwei uses improved whale algorithm to optimize the application of nuclear limit learning machine in water quality spectral analysis [17]. Although WOA algorithm has good optimization ability, whale optimization algorithm also has some shortcomings of other swarm intelligence algorithms. WOA algorithm has the disadvantages of low accuracy and slow convergence in dealing with complex optimization problems [18]. WOA is a group intelligence optimization algorithm based on the meta-heuristic. Like other group intelligence algorithms, it is easy to fall into the local optimal solution, resulting in slow convergence speed and low convergence accuracy in the later stage, especially for large-scale multi-peak function optimization [19].

To overcome WOA's shortcomings, several scholars have improved WOA. Lin chunwei (2019) introduced Levy flight into the whale algorithm to optimize and solve the problem of spectral analysis of water quality [17]. Sun et al. (2018) proposed a whale algorithm combining Levy flight and quadratic interpolation to solve large-scale global optimization problems [20]. Huang yuanchun(2019) proposed a strategy to improve the whale algorithm by using gauss–cauchy-hybrid variation, and established the tripping time prediction model [21]. Xu yufei et al. (2018) proposed an improved whale algorithm combining differential evolution and elite reverse learning for the optimization of residuum hydrogenation parameters [22]. Sahu et al. (2018) proposed the MWOA algorithm to coordinate the balance between the development stage and the exploration stage of the original whale optimization algorithm for SSSC controller optimization to improve the stability of the power system [23]. Niu (2017) introduced the whale optimization algorithm of reverse learning adaptive strategy, but its convergence speed is slow to some extent [24]. KAVEH A (2017) proposed to enhance the adaptive WOA. Although the improved algorithm showed good performance in solving the truss size optimization problem, its stability was poor [25].SAYED G I (2016) used WOA to select the optimal feature subset of breast cancer diagnostic methods [26]. Parmar S A (2016) uses WOA to solve the optimal power flow (OPF) problem [27]. Kaur introducing chaos mapping into the whale algorithms such as (2018), 10 different chaotic mapping formula, introduced respectively, to improve the population initialization and iterative process, test results show that the chaos mapping precision of algorithm convergence has a modest increase, the Tent chaotic mapping is the best effect, but the convergence accuracy and convergence rate is still has very big rise space [28]. zhong (2017) proposed a stochastic control parameters, such as the improvement of the whale optimization algorithm (EWOA) , and joined the gaussian mutation operator perturbation on the current optimal individual variations, the test shows that the algorithm convergence speed in the two test function has a lot of ascension, and the convergence speed of the four test functions are up slightly, but the function test is less, test dimension is low, not the test of large-scale optimization problems [29]. In order to further improve the convergence speed and local search ability of whale optimization algorithm, this paper introduces the inertia weight of whale optimization algorithm into random factor on the basis of non-linear decreasing. Then, the random search mode of Levy flight is introduced into whale optimization algorithm. By combining the improved whale optimization algorithm with the supervised S_Kohonen network, this paper establishes a novel prediction model to judge whether a telephone marketing customer subscribes to a fixed deposit or not. Firstly, this paper uses single factor analysis to examine whether the indicators have a significant impact on the results of bank telemarketing. Then the binary Probit model is established for the indicators that have significant impact on marketing results, and the weak significant indicators are eliminated through the variable significance test.

The main contributions of this paper are as follows:

Chapter 1 introduces the significance of time deposit and various data mining techniques used by domestic and foreign scholars to predict marketing results. The second chapter mainly introduces the main methods used in this paper, and verifies the excellent performance of the improved whale optimization algorithm. Chapter three carries on the empirical analysis. Chapter four summarizes.

The innovation of this paper is as follows:

(1) The dynamic inertia factor and the random search of Levy flight are introduced into the whale optimization algorithm to improve the convergence accuracy of the whale optimization algorithm.

(2) By adding an input layer, the unsupervised Kohonen network is transformed into a supervised S_Kohonen network.
(3) An improved whale optimization algorithm is proposed to enhance the global and local search ability of the whale optimization algorithm. Then the S_Kohonen network prediction model is optimized by using the improved whale optimization algorithm and applied to the prediction of telephone marketing results.

2. Proposed method

2.1. Kohonen network

Kohonen network is a self-organizing competitive neural network proposed by Teuvo Kohonen, a professor at Helsinki University in Finland, in 1982. Kohonen network is an unsupervised learning network, which can automatically cluster according to environmental characteristics. Kohonen network adjusts the weights of the network by self-organizing feature mapping, so that the network converges to a representation form. Kohonen network consists of two parts: input layer and competition layer. The first layer is input layer. The number of neurons in input layer is consistent with the index dimension of input sample. The number of nodes in input layer is m. The second layer is competition layer. The distribution of nodes in the competition layer is two-dimensional array distribution. The number of nodes in the competition layer is n. Then the weights of input layer and competition layer can be expressed as $w_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$.

The working mechanism of Kohonen network: When the samples are transferred from the input layer to the competitive layer, the neurons in the competitive layer calculate the Euclidean distance between the weights of the input samples and the neurons in the competitive layer, and select the neurons with the smallest distance from the input samples as the winning neurons. By adjusting the weights of the winning neurons and their peripheral neurons, the weights of the winning neurons and their peripheral neurons are close to the input sample. By repeatedly training the weights of neurons in the competitive layer, the weights of each neuron in the competitive layer eventually have a certain distribution, which can distribute the similar neurons to the representative neurons. The weights of the same kind of neurons are similar, and the weights of different kinds of neurons are quite different. Where $\mathrm{r(t)} \in [\mathrm{r_{min}}, \mathrm{r_{max}}]$ is the neighborhood radius, the neuron whose distance from the winning neuron is less than the neighborhood radius is the neighborhood neuron of the winning neuron. The weight of the neuron needs to be adjusted.

The adjustment formula is as follows:

$$w_{ij}(t) = w_{ij}(t-1) + \eta(t) \times (X_i - w_{ij}(t-1)) \quad t \neq 1 \tag{1}$$

$$\eta(t) = \eta_{\min} - \frac{t}{T} \times (\eta_{\max} - \eta_{\min}) \tag{2}$$

$$r(t) = r_{\max} - \frac{t}{T} \times (r_{\max} - r_{\min}) \tag{3}$$

$X_i(i = 1, 2, \ldots, m)$ is the input vector and $\eta(t)$ is the learning rate. Typically, $\eta(t) \in [\eta_{\min}, \eta_{\max}]$ decreases as the number of iterations increases. t is the current number of iterations and T is the maximum number of iterations.

2.2. S_Kohonen network

The advantage of Kohonen network is that it can classify unknown classified data unsupervised, but because the number of network nodes in the competition layer is much larger than the actual sample data category, it is easy to cause the same class of data to correspond to different network nodes, and it is easy to produce multiple different categories, which is accurate for the test data. Classification has had a negative impact. In this paper, Kohonen network is transformed into a supervised learning network (S_Kohonen) by adding an output layer after the competition layer [1]. An output layer is added behind the competition layer. The output layer is connected with the competition layer by weight. The number of nodes in the output layer is equal to the total number of categories of data. The weight adjustment formula between the competition layer and the output layer is as follows:

$$w_{jk}(t) = w_{jk}(t-1) + \eta_2(t) \times (Y_k - w_{jk}(t-1)) \quad t \neq 1 \tag{4}$$

$$\eta_2(t) = \eta_{2\min} + \frac{t}{T} \times (\eta_{2\max} - \eta_{2\min}) \tag{5}$$

In the formula $\eta_2(t)$ is the learning rate, which increases with the number of iterations. w_{jk} is the weights from the competition layer to the output layer, and the initial weights are chosen randomly. Y_k is the output result.

After network training, the test data can be classified. Firstly, the nearest competing layer node with the test sample is calculated as the winning node, and the output layer node with the largest weights connected to the winning node is the representative class of the test sample.

2.3. Traditional whale optimization algorithm (WOA)

Whale optimization algorithm (WOA) is a new optimization model proposed by Mirjalili S in 2016 by simulating whale predation behavior. Whale foraging is accomplished by creating unique bubbles on a circular or "9" path. Whales dive below the fish flock, climb up along the spiral path and approach the target fish flock. In the process of rising, they form a large net of bubbles to wrap the fish flock. The fish flock cannot escape the bubble barrier, and are finally killed by humpback whales. A whale optimization algorithm is proposed based on the whale predation method. The whale optimization algorithm mainly includes three mechanisms: shrinkage encirclement, spiral update and random search.

In order to describe this predation strategy, the following mathematical models are established:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}*(t) - \vec{X}(t) \right| \tag{6}$$

$$\vec{\mathrm{X}}(t+1) = \vec{X}*(t) - \vec{A} \cdot \vec{D} \tag{7}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_2 - \vec{a} \tag{8}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{9}$$

$\vec{X}*$ is the optimal position vector, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, and $\vec{r}$ is the random vector in [0, 1] during the iteration process.

(1) Encircling prey

$\vec{a}$ is the control vector. With the increase of iteration times, $\vec{a}$decreases from 2 linearity to 0 [13]. t is the current iteration number, $T\max$ is the maximum iteration number. By reducing the vector $\vec{a}$, the population is simulated to be close to the prey and enclosed by contraction.

$$\vec{a} = 2 - 2 \times \frac{t}{T\max} \tag{10}$$

(2) Spiral updating position

A spiral equation is established between the position of whale and its prey to simulate the spiral motion of humpback whales.

$$\vec{X}(t+1) = \vec{D^t} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}*(t) \tag{11}$$

Among them $\vec{D^t} = \left|\vec{X}*(t) - \vec{X}(t)\right|$. $\vec{X}*$ is the optimal position vector, b is the constant of logarithmic spiral shape and l is the random number in $[-1, 1]$.

(3) Search for prey

Considering that the contraction mechanism and spiral swimming may be simultaneous when the whale preys, the selection probability between the contraction mechanism and the spiral model is 50% to update the position of the whale. Because in the hunting process, whales will search for prey randomly in addition to spiral swimming and contraction encirclement mechanism, so at that time $\left|\vec{A}\right| \geq 1$, whales searched for prey randomly according to each other's position. The formula of whale position change can be summarized as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}*(t) - \vec{A}\cdot\vec{D_1} & \left|\vec{A}\right| < 1, \text{rand} < 0.5 \\ \vec{X}_{\text{rand}}(t) - \vec{A}\cdot\vec{D_2} & \left|\vec{A}\right| \geq 1, \text{rand} < 0.5 \\ \vec{D_3^t}\cdot e^{bl}\cdot\cos(2\pi l) + \vec{X}*(t) & rand \geq 0.5 \end{cases} \tag{12}$$

The formulas for calculating the adjustment vector $\vec{D}$ are also different with the different ways of whale position change. The concrete formulas are as follows:

$$\begin{cases} \vec{D_1} = \left|\vec{C}\cdot\vec{X}*(t) - \vec{X}(t)\right| \\ \vec{D_2} = \left|\vec{C}\cdot\vec{X}_{\text{rand}}(t) - \vec{X}(t)\right| \\ \vec{D_3} = \left|\vec{X}*(t) - \vec{X}(t)\right| \end{cases} \tag{13}$$

2.4. Improved whale optimization algorithm(IWOA)

The traditional whale optimization algorithm uses fixed inertia weight, so with the increasing number of iterations, the traditional whale optimization algorithm cannot change the convergence speed according to the location of the population, and the fixed inertia weight is not conducive to the population jumping out of the local optimal solution [12]. Therefore, the dynamic inertia weight is introduced in this paper.

$$w(t) = w_{\min}/(w_{\max} - w_{\min}) \times r \times e^{-t/T\max} \tag{14}$$

The inertia weight is introduced into three position updating formulas of whale optimization algorithm, then formula (12) is changed to:

$$\vec{X}(t+1) = \begin{cases} w\times\vec{X}*(t) - \vec{A}\cdot\vec{D_1} & \left|\vec{A}\right| < 1, \text{rand} < 0.5 \\ w\times\vec{X}_{\text{rand}}(t) - \vec{A}\cdot\vec{D_2} & \left|\vec{A}\right| \geq 1, \text{rand} < 0.5 \\ \vec{D_3^t}\cdot e^{bl}\cdot\cos(2\pi l) + w\times\vec{X}*(t) & rand \geq 0.5 \end{cases} \tag{15}$$

Although the whale optimization algorithm has good global convergence ability, it still has some limitations in convergence speed and local search ability. Therefore, this paper introduces Random Search of Ryan Flight to update the final position of whale after each iteration. Levy flight is a random search based on Ryan distribution. In recent years, it is often used to improve other optimization algorithms such as cuckoo algorithm [14], particle swarm optimization [15]. Finally, simulation shows that the improved algorithm based on Levy flight is superior to the original optimization algorithm.

Table 1
Description of benchmark functions.

Function	Dimension	Range	$f_{\min}$
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100,100]	0
$f_2(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	[−10,10]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j\right)^2$	30	[−100,100]	0
$f_4(x) = \min_i \{\lvert x_i\rvert, 1 \leq i \leq n\}$	30	[−100,100]	0
$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + +(x_i - 1)^2]$	30	[−30,30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[−100,100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0, 1)$	30	[−1,28,1.28]	0

The position formula of WOA algorithm introduced by Levy Flight is changed to:

$$\vec{X}(t+1) = \vec{X}(t) + (2\times rand - 1) * Levy(\lambda) \tag{16}$$

Where $Levy(\lambda)$ is a random search path and satisfies:

$$Levy \sim u = t^{-\lambda} 1 \quad < \lambda \leq 3 \tag{17}$$

The IWOA algorithm is described as follows:

2.5. Experimental simulation and result analysis

In order to verify the performance of improved whale optimization algorithm (IWOA), this paper compares the improved whale optimization algorithm with gravity search algorithm (GSA), particle swarm optimization (PSO), Gray Wolf algorithm (GWO), original whale optimization algorithm (WOA) and improved
whale optimization algorithm (LWOA) in reference 12. In this paper, seven typical benchmark function optimization problems are selected to verify [13]. Table 1 describes seven benchmark functions.

In order to make the algorithm comparable, this paper tries to make the parameter settings of each algorithm consistent. Specific parameters are set as follows: the population size of each algorithm is 30, and the maximum number of iterations is 500. The learning factor of PSO is set$C_1 = C_2 = 2$ and the weight factor$w \in [0.4, 0.9]$. Weight factor $w \in [0.4, 0.8]$ in LWOA and IWOA. For each test function, each algorithm runs 30 times, and then judges the optimization performance of each algorithm according to the average value and standard deviation of each function test. Specific test results are shown in Table 2.

From Fig. 1, we can see the two-dimensional images of functions $f_1(x)$ to $f_7(x)$, which can be used to evaluate the optimization capability of the algorithms proposed in this paper. As can be seen from Table 1, IWOA is very competitive with other meta-heuristic algorithms. Especially in the optimization of $f_1(x), f_2(x), f_3(x), f_4(x), f_7(x)$ functions, the performance results are the best. In the optimization of $f_5(x), f_6(x)$ functions, it still shows better performance than most optimizers. Therefore, the improved algorithm has a good use value.

Algorithm 1 Improved whale optimization algorithm (IWOA)

Initialize the whales population Xi(i = 1, 2, ..., n)
Calculate the fitness of each search agent
X=the best search agent*
while*(t < maximum number of iterations)*
for *each search agent*
Update a, A, C, l, and p
if1 *(p<0.5)*
if2 *(|A|< 1)*
Update the position of the current search agent by the Eq.(6)
else if2*(|A|>=1)*
Select a random search agent ()
Update the position of the current search agent by the Eq.(15)
end if2
else if1 *(p>=0.5)*
Update the position of the current search by the Eq. (15)
end if1
end for *Introducing Levy Random Flight by the Eq.(16)*
Check if any search agent goes beyond the search space and amend it
Calculate the fitness of each search agent
Update X if there is a better solution*
t=t+1
end while
*return X**

Table 2
Comparison of optimization results.

F	GSA		WOA		PSO		GWO		LWOA		IWOA	
	ave	std	ave	std	ave	std	ave	std	ave	std	ave	std
$f_1(x)$	2.88E−16	2.14E−16	5.67E−74	3.10E−73	0.000136	0.000202	8.26E−28	9.78E−28	9.38E−61	3.71E−60	1.64E−204	0
$f_2(x)$	0.049	0.267	3.95E−51	1.11E−50	0.042144	0.045421	1.01E−16	5.97E−17	3.87E−45	1.96E−44	2.207E−107	1.21E−106
$f_3(x)$	1017.81	276.58	4522.00	1390.72	70.121	22.124	1.44E−5	4.88E−5	8.35E−16	1.89E−16	6.61E−145	3.62E−144
$f_4(x)$	7.104	2.259	49.43	26.47	1.086	0.317	4.97E−7	3.57E−7	6.17E−9	1.66E−9	1.23E−82	6.74E−82
$f_5(x)$	70.359	73.742	28.02	0.51	96.718	60.115	27.233	0.707	28.821	0.041	28.265	0.403
$f_6(x)$	0.00975	0.0534	3.116	0.532	0.000102	82.28E−5	0.772	0.445	4.169	0.846	1.753	0.766
$f_7(x)$	0.083	0.043	0.004	0.005	0.123	0.045	0.0021	0.0011	7.99E−4	6.98E−4	6.78E−5	6.14E−5

Table 3
Data sets characteristics.

Data set	Patterns	Features	Classes	Test	Missing value
Iris	150	4	3	60	0
Seed	210	7	3	60	0
Network attack	4500	38	5	500	0

3. Experimental validation

In this paper, two benchmark data sets are used to evaluate the performance of the proposed IWOA-S_Kohonen algorithm. The data sets and their characteristics, the number of patterns, the number of features and the number of classes are given in Table 3.

As can be seen from Table 4, IWOA-S_kohonen algorithm achieves better results on Iris, Seed and Network attack data sets. The results show that IWOA algorithm can effectively optimize parameters. In addition, in terms of time efficiency, the running time of IWOA-S_kohonen algorithm is smaller than that of GA-S_kohonen algorithm. Therefore, IWOA algorithm can be used to optimize S_Kohonen model to obtain better classification performance than GA algorithm. As can be seen from Table 5, although the running time of CRT and support vector machine is significantly less than that of IWOA-S_kohonen, it can be seen from the classification results of sample Iris and seed that the classification error of IWOA-S_kohonen algorithm is significantly less than that of CRT and support vector machine, so IWOA-S_kohonen algorithm is worth using lower time requirements in classification.

4. Prediction and Analysis of S_Kohonen Network Telephone Marketing Results Based on IWOA

4.1. Data sets

The data used in this paper are 41188 telephone time deposit marketing activities data from Portuguese banking institutions in UCI website. The purpose of this study is to make a prediction of whether customers subscribe to bank time deposits. Therefore, the response variable is a two-class variable, with the subscription mark being 1 and the non-subscription mark being 0. The data source is https://archive.ics.uci.edu/ml/index.php. In the 41188 customer data, 36549 customers did not order

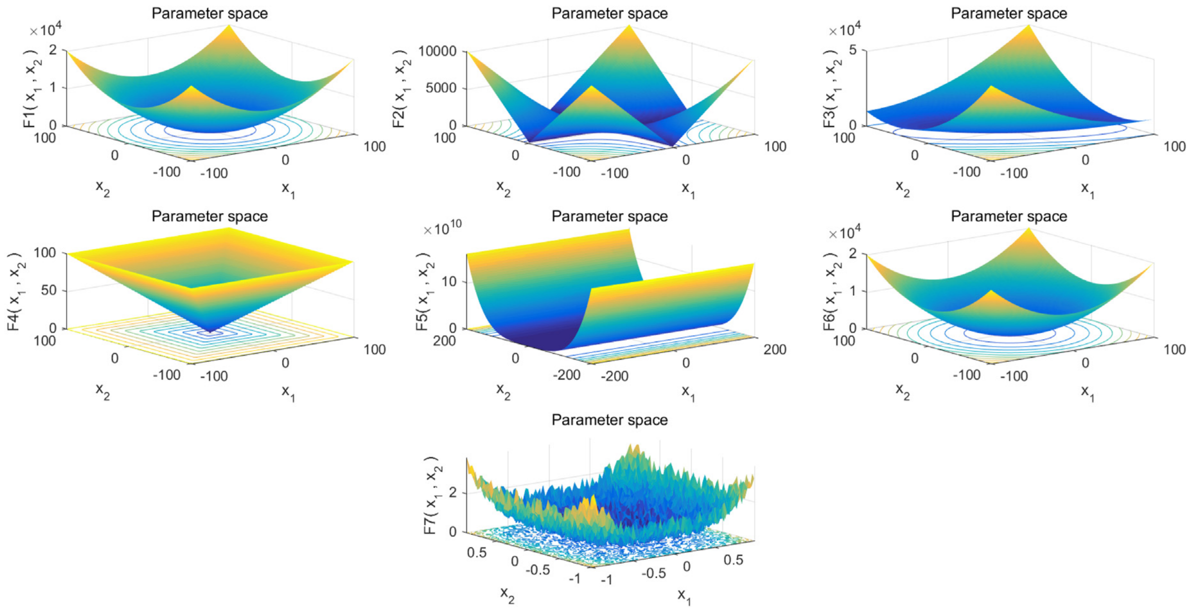

Fig. 1. Typical 2D representations of benchmark mathematical functions.

Table 4
Comparison results.

Data set	Population	IWOA-S_Kohonen	Time	GA-S_Kohonen	Time
Iris	5	0.01667	149.961 s	0.06667	177.035 s
	10	0	301.123 s	0.06667	348.268 s
	15	0	449.726 s	0.06667	471.427 s
	20	0	57.361 s	0.06667	627.101 s
Seed	5	0.0667	156.733 s	0.15	166.037 s
	10	0.05	309.976 s	0.1167	329.827 s
	15	0.05	443.089 s	0.1167	476.280 s
	20	0.05	594.962 s	0.05	641.901 s
Network attack	5	0	160.209 s	0.032	180.231 s
	10	0	312.103 s	0.02	332.452 s
	15	0	450.132 s	0.02	498.123 s
	20	0	600.121 s	0.02	623.854 s

time deposits, which is 7.9 times that of the ordering customers. So the data is unbalanced. So this paper uses the method of bottom sampling to select 5361 samples from the non-ordering customers, and composes 10 000 data with 4639 samples as the experimental data of this paper.

4.2. Index selection of sample set

This paper chooses 10,000 experimental data, including 20 indicators affecting customer's time deposit order and 1 target vector. The continuous indicators are as follows: Age X1, last contact duration (Duration) X2, number of contacts performed during this campaign and for this client (campaign) X3, number of days that passed by after the client was last contacted from a previous campaign (pdays) X4, number of contacts performed before this campaign and for this client (previous) X5, employment variation rate X6, consumer price index (cons.price.idx) X7, consumer confidence index (cons.conf.idx) X8, euribor 3 month rate (euribor3m) X9, number of employees X10. Classification indicators: type of work X11, marital status X12, education X13, credit default X14, housing loan X15, personal loan X16, contact mode X17, last contact month of year (month) X18, last contact day of the week (day_of_week) X19, outcome of the previous marketing campaign (poutcome) X20. We include tables describing the various variables in Table 6. Due to the complexity and diversity of factors affecting customers'time deposit orders, there may be multiple collinearities among these factors. If banks do not selectively introduce many factors to predict time deposit orders, they often fail to achieve good prediction results, or even make wrong decisions. Therefore, this paper first carries out a single factor analysis of these indicators, examines whether there are significant differences between the indicators and the results of bank telemarketing, and then establishes a binary Probit model for the indicators that have significant differences with the results of marketing, and eliminates the weak significant indicators through the test of variable significance.

Table 5
Comparison Results.

	CRT	Time	SVM	Time
Iris	0.1667	1.443 s	0.0333	21.615 s
Seed	0.1333	10.813 s	0.11667	34.147 s
Network attack	0	15.333360 s	0.02	36.630337s

4.3. Chi-square test

type of work X11, marital status X12, education X13, credit default X14, housing loan X15, personal loan X16, contact mode X17, last contact month of year (month) X18, last contact day of the week (day_of_week) X19, outcome of the previous marketing campaign (outcome) X20. These 10 variables are classified variables, so chi-square test is chosen (see Table 7).

Table 6
Data set index description data.

Age X1	Continuous variable	(cons.conf.idx) X8	Continuous variable	Housing loan X15	Classified variable
Last contact duration (Duration) X2	Continuous variable	(euribor3m) X9	Continuous variable	Personal loan X16	Classified variable
(campaign) X3	Continuous variable	Number of employees X10	Continuous variable	Contact mode X17	Classified variable
(pdays) X4	Continuous variable	type of work X11	Classified variable	Last contact month of year (month) X18	Classified variable
(previous) X5	Continuous variable	marital status X12	Classified variable	(day_of_week) X19	Classified variable
Employment variation rate X6	Continuous variable	education X13	Classified variable	(poutcome) X20	Classified variable
Consumer price index (cons.price.idx) X7	Continuous variable	Credit default X14	Classified variable		

Chi-square test by Spss software shows that whether there is personal loan or housing loan, the two classification indicators P > 0.05 (black font in the table), indicating that there is no statistical significance between the success of marketing and the two indicators.

4.4. T test

Age X1, last contact duration (Duration) X2, number of contacts performed during this campaign and for this client (campaign) X3,number of days that passed by after the client was last contacted from a previous campaign (pdays) X4, number of contacts performed before this campaign and for this client (previous) X5, employment variation rate X6, consumer price index (cons.price.idx) X7, consumer confidence index (cons.conf.idx) X8, euribor 3 month rate (euribor3m) X9, number of employees X10. These 10 variables are continuous variables, so the t test of two independent samples is carried out. The test results are as shown in Table 4.

Table 8 shows that there is no significant difference in the age of marketing success. P = 0.192 > 0.05 (lines with P value greater than 0.05 have been blackened in the table) shows that there is no significant difference in the age of marketing success.

4.5. Establishment of binary probit model

Through univariate analysis, the Zuo binary Probit regression equation of 17 indicators, such as marital status and job type, is taken as an independent variable, and the dependent variable is whether marketing is successful or not. It further explains the fitting degree of the model and the significant influence degree of each index on the success of marketing. Table 9 is the output (rows with a P value greater than 0.05 have been blackened in the table).

From the LR=0 in Table 9, we can see that the model can well fit the observed data. By fitting the significance of the variables obtained from the model, we can find that the P values of the other 13 variables are less than 0.05 except X5, X11, X12 and X19, which indicates the type of education and whether there has been credit default. Thirteen variables have a significant impact on the success of marketing.

4.6. Empirical test

4.6.1. Operating environment and complexity analysis

In this paper we use the same computer, the same software to run the algorithm. In addition, in the optimization algorithm, the search population and the maximum iteration times are consistent, which makes it more convenient to observe the optimization ability and convergence of each intelligent algorithm population. In the process of classification, each algorithm is compared with the same training data and prediction data, so as to avoid the evaluation error caused by different data.

This paper uses IWOA algorithm to optimize S_Kohonen network. The competition layer of S_Kohonen network is set to 8*8 in this paper. In order to compare and improve the performance of the whale optimization algorithm, this paper tries to keep the parameters consistent, so the number of population in the whale optimization algorithm and the genetic algorithm is 10, and the maximum number of iterations is 35. This test environment: Core i5-3230M dual-core processor, running in the 2016a version of matlab.

In this paper, the frequency estimation method is used to analyze the computational time and space complexity of the improved whale algorithm. In this paper, the maximum number of iterations is set as T, the population size is pop, and the dimension of the variable is dim. As can be seen from Section 2.4, the statement execution frequency of the innermost loop body is all $T(n) = O(f(n)) = O(T \cdot pop \cdot \mathrm{dim})$. In the algorithm, the variable storage space is affected by pop of population size and dim of variable dimension, so its spatial complexity can be expressed as $S(n) = O(f(n)) = O(pop \cdot \mathrm{dim})$.

4.6.2. Comparative analysis of forecasting examples

Finally, 13 variables, such as education type and credit default, are used as input of S_Kohonen network, and marketing success is used as output to predict marketing results. Then the S_Kohonen network is optimized by GA algorithm, WOA algorithm, IWOA algorithm and LWOA algorithm in reference 12. Finally, the prediction effect of S_Kohonen network is tested by simulation results, and the performance of IWOA algorithm in optimizing S_Kohonen network is tested.

In this paper, the GA-S_Kohonen network, SVM, LWOA-S_Kohonen network, IWOA-S_Kohonen network and S_Kohonen network are tested by 10 fold crossover. Fig. 2 shows the accuracy test results of five test models.

Table 7
Chi-square test for categorized variables.

Variable	Variable value	Yes (N=4640)	No (5360)	χ^2	P
X_{12}	Divorced	476(43.8%)	610(56.2%)	82.433	0.000
	married	2532(43.3%)	3311(56.7%)		
	Single	1620(53.1%)	1433(46.9%)		
	Unknown	12(66.7%)	6(33.3%)		
X_{11}	Admin	1352(50.1%)	1345(49.9%)	456.082	0.000
	Blue-collar	638(33.9%)	1242(66.1%)		
	Entrepreneur	124(36.6%)	215(63.4%)		
	Housemaid	106(46.7%)	121(53.3%)		
	Management	328(48.1%)	354(51.9%)		
	Retired	434(71.1%)	176(28.9%)		
	Self-employed	149(42.7%)	200(57.3%)		
	Services	323(37.2%)	546(62.8%)		
	Student	275(75.3%)	90(24.7%)		
	Technician	730(44.9%)	896(55.1%)		
	Unemployed	144(51.8%)	134(48.2%)		
	Unknown	37(46.4%)	41(53.6%)		
X_{13}	Basic.4y	428(43.8%)	550(56.2%)	147.137	0.000
	Basic.6y	188(37.9%)	308(62.1%)		
	Basic.9y	473(35.9%)	844(64.1%)		
	High school	1031(44.3%)	1295(55.7%)		
	illiterate	4(50%)	4(50%)		
	Professionalcourse	595(47.3%)	664(52.7%)		
	Universitydegree	1670(52.7%)	1497(47.3%)		
	Unknown	251(55.9%)	198(44.1%)		
X_{14}	Yes	443(27.1%)	1192(72.9%)	294.924	0.000
	No	4197(50.2%)	4166(49.8%)		
	Unknown	0(0%)	2(100%)		
X_{15}	Yes	2507(47%)	2825(53%)	2.342	**0.310**
	No	2026(45.6%)	2420(54.4%)		
	Unknown	107(48.2%)	115(51.8%)		
X_{16}	Yes	683(45.8%)	809(54.2%)	0.535	**0.765**
	No	3850(46.5%)	4436(53.5%)		
	Unknown	107(48.2%)	115(51.8%)		
X_{17}	Cellular	3853(54.1%)	3268(45.9%)	590.815	0.000
	Telephone	787(27.3%)	2092(72.7%)		
X_{18}	3	276(87.1%)	41(12.9%)	1024.03	0.000
	4	539(62.9%)	318(37.1%)		
	5	886(31.9%)	1890(68.1%)		
	6	559(44.4%)	700(55.6%)		
	7	649(40.1%)	968(59.9%)		
	8	655(45%)	802(55%)		
	9	256(84.8%)	46(15.2%)		
	10	315(82.9%)	65(17.1%)		
	11	416(44.5%)	519(55.5%)		
	12	89(89%)	11(11%)		
X_{19}	1	847(43.3%)	1109(52.3%)	21.020	0.000
	2	953(47.7%)	1044(52.3%)		
	3	949(47.4%)	1054(52.6%)		
	4	1045(49.2%)	1077(50.8%)		
	5	846(44%)	1076(56%)		
X_{20}	Failure	605(53.2%)	532(46.8%)	993.344	0.000
	nonexistent	3141(39.8%)	4758(60.2%)		
	Success	894(92.7%)	70(7.3%)		

Table 8
T-test of two independent samples.

	N	Average	Standard deviations	Minimum	Maximum	P
X_1	**10000**	**40.2945**	**11.8505**	**17.00**	**98.00**	**0.192**
X_6	10000	−.4335	1.71821	−3.40	1.40	0.000
X_4	10000	894.7338	304.42874	.00	999.00	0.000
X_3	10000	2.3774	2.47285	1.00	42.00	0.000
X_5	10000	.2993	.68042	.00	6.00	0.000
X_2	10000	374.2986	354.08497	3.00	4199.00	0.000
X_7	10000	93.4910	.62957	92.20	94.77	0.000
X_8	10000	−40.2230	5.29829	−50.80	−26.90	0.000
X_9	10000	3.0330	1.88674	.63	5.05	0.000
X_{10}	10000	5138.7316	86.17423	4963.60	5228.10	0.000
Whether the marketing is successful or not	10000	.4640	.49873	.00	1.00	0.000

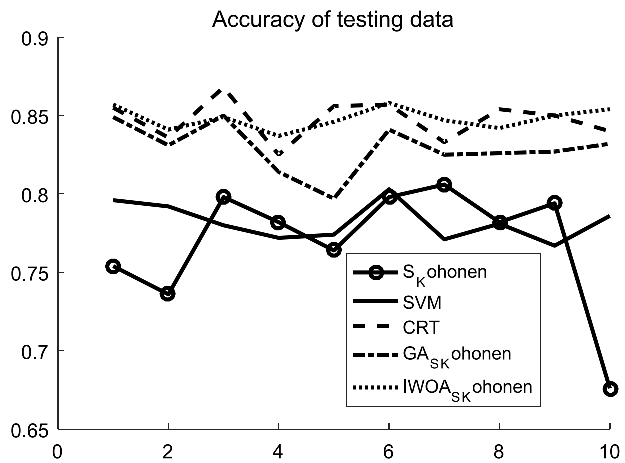

Fig. 2. 10 Cross-check Accuracy Test Results.

Table 9
Significance of different indicators.

Variable	Coefficient	Std.Error	z-Statistic	Prob.
X_2	0.003103	2.27E−05	49.52761	0.0000
X_3	−0.017667	0.008609	−2.052187	0.0402
X_4	−0.000478	0.000163	−2.938607	0.0033
$\mathbf{X_5}$	**0.0009425**	**0.059211**	**0.159174**	**0.8735**
X_6	−0.743985	0.061035	−12.18955	0.0000
X_7	0.595982	0.087499	6.811297	0.0000
X_8	0.017651	0.004820	3.661986	0.0003
X_9	0.377033	0.081884	4.604491	0.0000
X_{10}	−0.004761	0.001320	−3.605789	0.0003
$\mathbf{X_{11}}$	**0.004899**	**0.004604**	**1.064141**	**0.2873**
$\mathbf{X_{12}}$	**0.033481**	**0.027091**	**1.235843**	**0.2165**
X_{13}	0.049819	0.008095	6.154098	0.0000
X_{14}	−0.242651	0.050229	−4.830926	0.0000
X_{17}	−0.507733	0.054744	−9.274716	0.0000
X_{18}	−0.021451	0.010584	−2.026810	0.0427
$\mathbf{X_{19}}$	**−0.000220**	**0.011761**	**−0.018668**	**0.9851**
X_{20}	0.353490	0.074486	4.745741	0.0000
LR statistic	0.000000			
Pseudo R2	0.473396			

Table 10
Sample data description.

Result type	code	Total number of samples
success	1	4639
failure	2	5361
Total	–	10000

From Fig. 2, we can see that the prediction accuracy of S_Kohonen network optimized by weight is almost higher than 80%, which is significantly higher than that of S_Kohonen network without weight optimization. Therefore, it can be shown that the method of using swarm intelligence algorithm to optimize S_Kohonen network is feasible. In order to illustrate the performance of IWOA algorithm more clearly, 1000 samples are randomly selected as test data, and the remaining 9000 samples are used as training data. The results of five prediction models are compared. In order to accurately predict the results of bank telemarketing, this paper randomly extracts test samples from each type . The coding of the specific results and the number of samples are shown in Table 10.

In this paper, the experimental algorithm is compared by 10 fold method, and the time information is provided. Because the test samples produced in each experiment are random, this paper runs 10 times on five test models, and the test samples of each five models are the same as the training samples. The error results of 10 tests of five models are shown in Table 11 (adding black fonts in the table is the minimum error of a single test).

From Table 11, it can be seen that the classification error of the experiment by using IWOA and GA optimized S_Kohonen network is less than the prediction error of S_Kohonen network, which shows that the prediction effect of the optimized S_Kohonen network is better than that of the unoptimized S_Kohonen network. Although it can be seen from Table 11 that IWOA optimized S_Kohonen network consumes longer time, the prediction accuracy is better than the other four prediction models, so IWOA-S_Kohonen model can be used in the engineering with less time requirement but higher precision requirement.

Based on Friedman's test and Nemenyi's statistical test

1. Friedman test

To verify the significant difference in classifier performance, This paper conducts Friedman's test and Nemenyi's statistical test on the error results of each algorithm in Table 11. The Friedman test is a nonparametric statistical significance test that is widely used to compare multiple algorithms, using their performance samples to identify significant differences between them [30]. For k algorithms and N data sets, first get the test performance results of each algorithm on each data set, then sort according to the performance from good to bad, and give the sort value $1, 2, \ldots, k$, If the performance results of multiple algorithms are the same, then they share the value of the sort equally. Assuming that the average ranking value of the ith algorithm is R_i, R_i follows a normal distribution, and the variable τ_F follows the distribution of F with degrees of freedom of k-1 and (k-1) (n-1) :

$$\tau_{x^2} = \frac{12n}{k(k+1)}\left[\sum_j R_j^2 - \frac{k(k+1)^2}{4}\right] \tag{18}$$

$$\tau_F = \frac{(n-1)\tau_{x^2}}{n(k-1)-\tau_{x^2}} \tag{19}$$

In this paper, the test result of one data was conducted by Friedman test with Spss. Under the condition of significance level of 0.05 and confidence interval of 95%, the final result showed that P value was less than 0.001, the test statistic was 99.405, rejecting the null hypothesis. Then, it shows that the performance of the algorithms is significantly different, and it is necessary to carry out follow-up tests to further distinguish the algorithms. Nemenyi's post-interim test is used to report significant differences between the various classifiers.

Nemenyi test

According to Nemenyi post-self-organization test, if the average grade of the two classifiers is different, their performance is significantly different, and the calculation results are as follows.

$$CD = q_\alpha\sqrt{\frac{k(k+1)}{6N}} \tag{20}$$

q_α in formula Eq. (20) refer to Table 12.

If the sorting value of any two algorithms is greater than CD, the performance of the two algorithms is significantly different. Sorting by the results of different algorithms, we further made the Friedman diagram, as shown in Fig. 3.

For the Friedman diagram, if there is no overlap between the two algorithms, there is a significant difference between the two algorithms. It can be seen from Fig. 3 that the performance of SVM algorithm and S_Kohonen algorithm are significantly different from that of IWOA_S_Kohonen, GA_S_Kohonen, and CRT. Further performance ranking shows that the performance of the optimized S_Kohonen network is significantly improved.

Table 11
Error results.

	S_Kohonen	SVM	CRT	GA-S_Kohonen	IWOA-S_Kohonen
	0.246	0.204	0.145	0.151	**0.143**
	0.264	0.208	0.164	0.169	**0.159**
	0.202	0.22	**0.132**	0.15	0.151
	0.218	0.228	0.175	0.186	**0.163**
	0.236	0.226	**0.144**	0.203	0.154
	0.202	0.197	0.143	0.159	**0.142**
	0.194	0.229	0.167	0.175	**0.153**
	0.218	0.219	**0.146**	0.174	0.158
	0.206	0.233	**0.15**	0.173	**0.15**
	0.324	0.214	0.16	0.168	**0.146**
Mean time	6.934 s	79.173 s	2.063 s	32 min25 s	31 min31 s

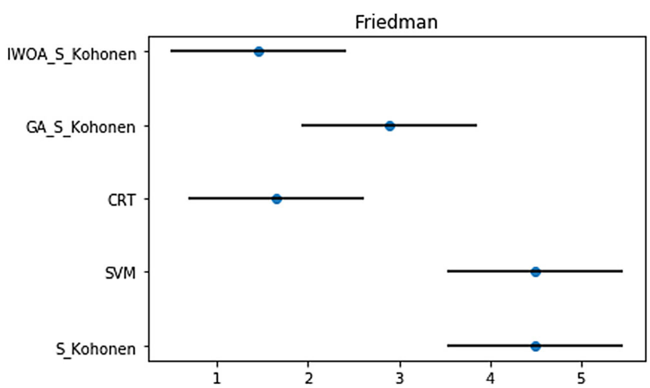

Fig. 3. Friedman Chart.

Table 12
The value table for q_α.

α	K								
	2	3	4	5	6	7	8	9	10
0.05	1.960	2.344	2.569	2.728	2.850	2.949	3.031	3.102	3.164
0.1	1.645	2.052	2.291	2.459	2.589	2.693	2.780	2.855	2.920

5. Conclusion

Time deposit plays an important role in the stability of banks. How to increase the number of customers to choose time deposit has become the primary marketing purpose of major banks. Telemarketing is the main marketing method with its low cost and low time-consuming. Identifying potential users accurately can not only improve the success rate of telemarketing and enhance the competitiveness of the industry, but also avoid harassing other customers, thus contributing to future marketing. Therefore, how to predict the results of telephone marketing quickly and accurately is the key to ensure that a bank can become a leader in the industry.

In this paper, an improved whale optimization algorithm is proposed to optimize the prediction model of S_Kohonen network to realize the prediction of bank telemarketing results, which can effectively identify potential customers. Finally, the empirical results show that the prediction accuracy of S_Kohonen network after weight optimization is significantly higher than that of S_Kohonen network. The prediction accuracy of S_Kohonen network optimized by the improved whale optimization algorithm is higher than that of S_Kohonen network optimized by genetic algorithm, traditional whale optimization algorithm and *12* refs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Chun Yan: Conceptualization, Methodology, Supervision, Writing - original draft. **Meixuan Li:** Software, Validation. **Wei Liu:** Project administration.

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