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Support vector machine applied in the agriculture of Fanjing Mountain Areas

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Abstract. The method of Support Vector Machine (SVM) in Machine Learning (ML) has the advantages of complete theory, strong adaptability, global optimization, short training time and good generalization performance, which has become a hot topic in international and domestic research. Therefore, it is of great meaning to apply SVM to the modernization and intellectualization agriculture of Fanjing Mountain Areas of Tongren city, Guizhou province. This article introduces the basic situation of Fanjing Mountain Areas's agriculture in Section I. Section II and III expounds the method of kernel and four multi-class SVMs respectively. A practical application case about the shape classification problem of "clenched fist" in SVM is done in Section IV, and finally Section V concludes the full text.

1. Introduction

Machine Learning (ML) is a core research field of artificial intelligence, which is of great significant research status and is also a branch of the most active and research value in Computer Science (CS). At present, ML technology not only plays an important role in the field of CS, but also becomes the key support technology of some interdisciplinary subjects [1]-[3]. And yet support vector machine (SVM) is a general machine learning algorithm (MLA), which was gradually developed since the 1990s. Its solid theory foundation can effectively solve the bottleneck problems, such as small sample, dimension disaster, local extremum, over-fitting, under-fitting, etc. Due to its remarkable performance, SVM has been successfully applied in numerous pattern recognition areas; for example, face recognition, remote sensing image analysis, spectral classification, handwriting recognition, fault identification and prediction, which fully demonstrate the great importance of ML on the one hand, and offers researchers plenty of opportunities on the other hand [4]-[5].

China is a big agricultural country and agriculture has always been the lifeblood of the national economy. In the context of the current new normal economy, rural agriculture faces numerous new challenges, such as shortage of agricultural resources, low productivity, international and domestic price inversion of agricultural products, the eco-environmental constraints, highlighted rural ageing, etc. Intellective agriculture takes ML, information perception equipment, communication network and the technology of intelligent information processing and Internet of Things (IOT) as the core, to implement agricultural scientific management, and to achieve purpose of the rational use of agricultural resources, the improvement of ecological environment, the reduction of production cost, and the enhancement of the yield and quality of agricultural products. In Fanjing Mountain Areas of Tongren city, Guizhou province, to construct the modernization and intellectualization of modern agricultural is the only way to raise the comprehensive ability of agricultural production, and to promote the transformation and upgrading of agriculture. Using the technology of IOT can fully exploit the agriculture data resources of Fanjing Mountain Areas and its advantage of the unique geographical environment, and building according to customer demand for dynamic adaptive smart agricultural services.

This paper aims at the development of modern agricultural in Fanjing Mountain Areas, utilizing all kinds of sensors to rapidly and completely acquire the growth of crops for the environment factors (such as soil temperature, soil moisture, air temperature, air humidity, light intensity and the concentration of carbon dioxide (CO2)), as well as the individual animals with biometric information (temperature, pulse, location information), and then using SVM in ML to classify the collected data, so the problem is transformed into the classification problem of SVM. The processed results will be timely feed back to personal computers (PCs), smartphones, and other terminal devices, thus it can help the general agricultural workers with immediate knowledge of the trends of growth conditions and environmental changes for crop growth, and provide users with a set of powerful, efficient and convenient agricultural monitoring solution.

2. The kernel method of function

The method of linear transformation can classify the two types for the above condition, but for the undivided linear problems, as shown in Fig. 1 (a), a straight line can not resolve the problem of classification. At this moment, the main idea is through the method of a nonlinear transformation $\phi(x)$ that maps it into a higher dimensional space, for example, each element of Fig. 1 (a) belongs one dimensional space that can be mapped into two dimensional space as shown in Fig. 1 (b) [5], which has resulted in a linearly separable problem in high dimension space. Moreover, only for inner product operation in high dimensional space, i.e., the original linear inner product (x_i, x_j) is changed to $(\phi(x_i), \phi(x_j))$, the form of nonlinear transformation does not even need to be known. So the problem of higher dimensional change calculation is avoided, and it greatly simplifies the original problem. According to the *Hilbert-Schmidt* principle, as long as an operation satisfies the *Mercer* condition [1], it can be used as an inner product function (or kernel function).

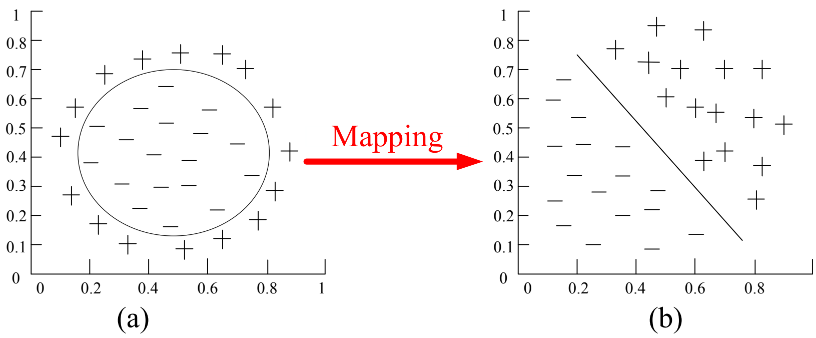

Figure 1. Mapping

Let $K(x_i, \mathbf{u}_*) = \phi(x_i) \cdot \phi(\mathbf{u}_*)$. Because $x_i \cdot \mathbf{u} = < x_i, \mathbf{u} >$, $\sum_{i=1}^{m} \alpha_i \cdot y_i \cdot x_i \cdot \mathbf{u} + \mathrm{b} \geq 0$, can be expressed as $\sum_{i=1}^{m} \alpha_i \cdot y_i \cdot K(x_i, \mathbf{u}_*) + \mathrm{b} \geq 0$, which just reflects the advantage of kernel method is that only knows what is its kernel function (i.e. inner product function). There are three main kernel functions [7], i.e., the kernel functions of polynomial, Radius Basis Function (RBF) and *Sigmoid*, their expression are

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$$K(x,y)=\left[(x\cdot y)+1\right]^q,\ K(x,y)=\exp\left\{-\frac{|x-y|^2}{2\sigma^2}\right\},\text{ and } K(x,y)=\tan h\{v(x\cdot y)+c\} \tag{1}$$

Different kernel functions can be selected for the problems of different classification, but there is not yet an effective method of selecting the optimal kernel function for a specific problem.

3. Multi-class SVMs

SVM is proposed for two kinds of problems, but in some practical applications, it is often to address multi-class problems. The problem of multiclass classification in mathematical language is [8]:
Given training set

$$T=\{(x_1,x_1),\cdots,(x_l,x_l)\}$$

Where $x_i\in R^n$, $y_i\in Y=\{1,\cdots,M\}$. To search a decision function $f(x)$ accordingly, give an accurate output category for any input vector x. Here are some algorithms for solving multiple class problems.

3.1. One-against-one

Through one-against-one approach, the problem of M-class classification is transformed into that of two-against-two classification, namely it needs to construct $M(M-1)/2$ classification hyper-plane. For all $(i,j)\in\{(i,j)\,|\,i<j, i\in Y, j\in Y\}$, a new training set T_{ij} can be obtained, in which the samples of the training set $y=i$ and $y=j$ are respectively used as positive sample points and negative sample points. Using two kinds of SVMs to classify the above training set, the decision function is g_{ij}. For a decision function that x belongs to i class means that the i class acquires a vote. Consider all of the above decision functions for the input x, the most popular category is the type of x. In this mode, two-two structures $M(M-1)/2$ classification hyper-planes, and the constructed multiple classifiers have high accuracy. As the number of categories increases, the number of super-planes needed to construct is also increasing rapidly, which increases the complexity of the algorithm. In Fig. 2, a one-to-one three-class classifier is presented in the two-dimensional plane.

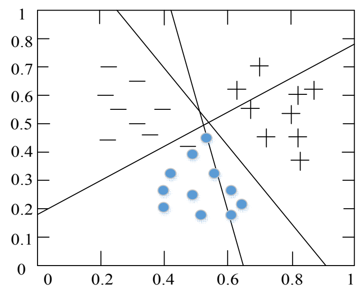


Figure 2. A one-to-one three-class classifier.

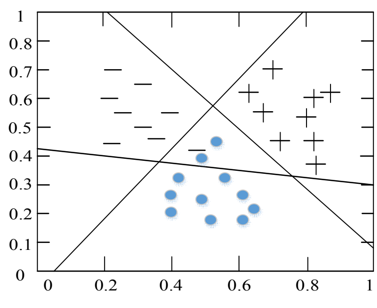


Figure 3. A one-to all three classifier.

3.2. One-against-all

For the M multi-class problems, construct classifiers between each category and all other $(M-1)$. For the i classifier, the category label for the training data should be re-modified, the data category of class i is recorded as +1, and the remaining data is all marked as -1. The quadratic programming of the classifier is solved as:

$$\begin{cases} \min \frac{1}{2}\left\|w^i\right\|^2 + C\sum_{j=1}^{l} \xi_j^i \\ s.t. \quad \left(w^i \cdot \varphi\left(x_j\right)\right) + b^i \geq 1 - \xi_j^i, \, i = j, i = 1, \cdots, l \\ \quad \left(w^i \cdot \varphi\left(x_j\right)\right) + b^i \leq 1 + \xi_j^i, \, i \neq j \\ \quad \xi_j^i \geq 0 \end{cases}$$

In the process of constructing multi-class classifier, the maximal category with output value of classification function is the prediction category:

$$f(x) = \underset{i=1,2,\cdots,M}{arg \max} \, sgn\left(\left(w^i \cdot \varphi(x)\right) + b^i\right) \tag{2}$$

Compared with the method of one-against-one, the algorithm of this method has lower complexity. However, the two types of questions considered are often not symmetric, positive and negative data are unbalanced, and the classification performance is poor. In addition, there exists a large number of in-separable points and has poorer generalization ability. Fig. 3 shows a one-to all three classifiers in a two-dimensional plane.

4. The application of SVM

In supervised learning algorithm so far, SVM is known for its powerful ability. On this issue, SVM is challenged by the classification problem of "clenched fist" as shown in Fig. 4 [1]. The radius of the three concentric circles is $d_1 = 0.2m$, $d_2 = 0.5m$ and $d_3 = 0.8m$, respectively. This paper does the following experiments for Fig. 5. Firstly, generate 100 rounds, randomly select 200 training samples per round, and produce the same test data for each of the two regions in Fig. 5. First, Secondly, set C=500, and train a SVM. Accordingly, the boundary of decision making is constructed by constructing the machine computation. Thirdly, test the network and determine the error rate of classification. Fourthly, repeat the above experiments for C=100 and C= 2500.

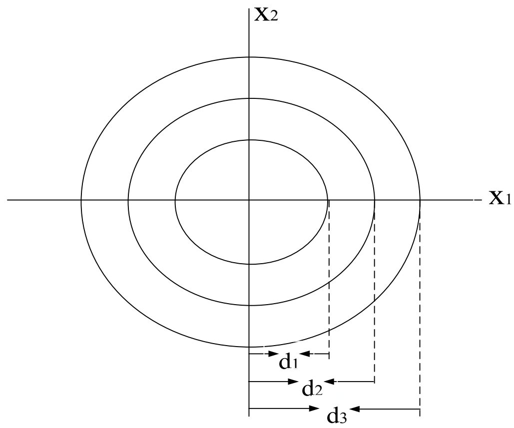
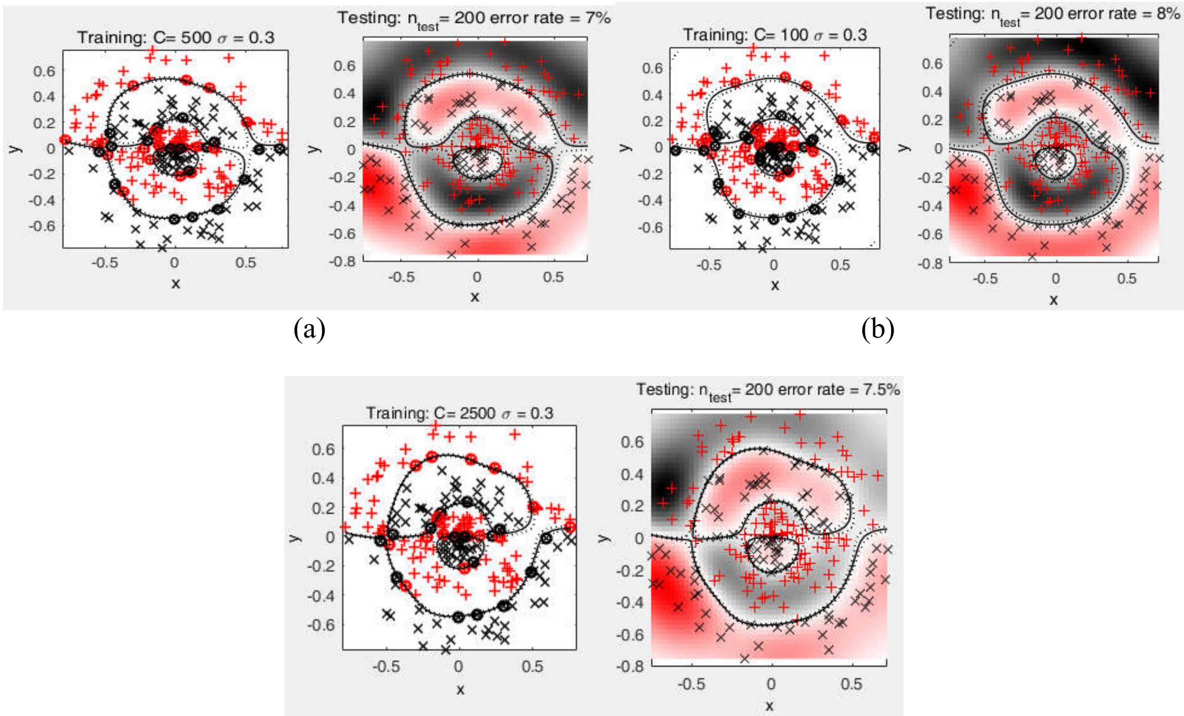


Figure 4. The shape of "clenched fist".



(a) (b)

(c)

Figure 5. The results of experiments.

In Fig. 5, the kernel function of Gaussian is used, and $\sigma = 0.3$. It can be seen from Fig. 5(a), (b) and (C) that when C=500, C=100, and C=2500, separately, the error rate is 7%, 8%, and 7.5%, respectively. The simulation results show that selecting the appropriate C can reduce the error rate to a minimum, which means C is neither too small nor too big.

5. Conclusion

In theory, SVM is a kind of strong classifiers with excellent generalization capabilities, compared with neural network and decision tree, etc., the learning machine is more stable. But in the process of application, there exists some unavoidable problems for SVM, such as, in order to reduce the time and space complexity of solving optimization problems, the approximation algorithm is needed; To address multiple problems, SVM is required to expand, etc. But these shortcomings lower the stability and generalization ability of SVM. In the future research work, we will find a new way to enhance the generalization ability and relative stability, and collect the agricultural data of Fanjing Mountain Areas, and conduct real-time analysis.

Acknowledgments

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