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Research Article

Research on Application of Support Vector Machine in Machine Learning

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Abstract: In recent years, support vector machine learning methods have gradually become the main research direction of machine learning. The support vector machine has a small structural risk compared with the traditional learning method, which can make the training error and the classifier capacity reach a relatively balanced state. Secondly, it also has the advantages of strong adaptability and strong promotion ability and has been widely praised by the industry. The following discussion focuses on the application of support vector machine in machine learning.

Keywords: Support Vector Machine, Machine Learning, Face Recognition, Image Preprocessing

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1 Introduction

At present, domestic personal credit consumption behaviors are increasing. Plus, personal credit lending platforms such as bank credit loans and Ant Check Later payment software are constantly emerging. Under this circumstance, personal credit evaluation has begun to receive the attention of the government and enterprises. The evaluation of personal credit has very important practical significance for reducing the credit risk loss of commercial banks and improving the efficiency of banks. Thus, stimulating the enthusiasm of ordinary consumers for credit loan applications and promoting the growth of China's economy.

2 Face recognition problem

SVM can also be called as support vector machine. In the rapid rise in process of science and technology development, it has become one of the key research topics in the field of machine learning. The support vector machine is effective and good in performance. One of the advantages of support vector machine is: it can avoid problems in the neural network. As an example, it is difficult to determine the network structure, etc., or the structure network is extremely small. When solving small sample data analysis and linear regression, the support vector machine shows great advantages and effects. Therefore, some people have taken advantage of the advantages of support vector machines to introduce them into new fields, such as the detection of face recognition.

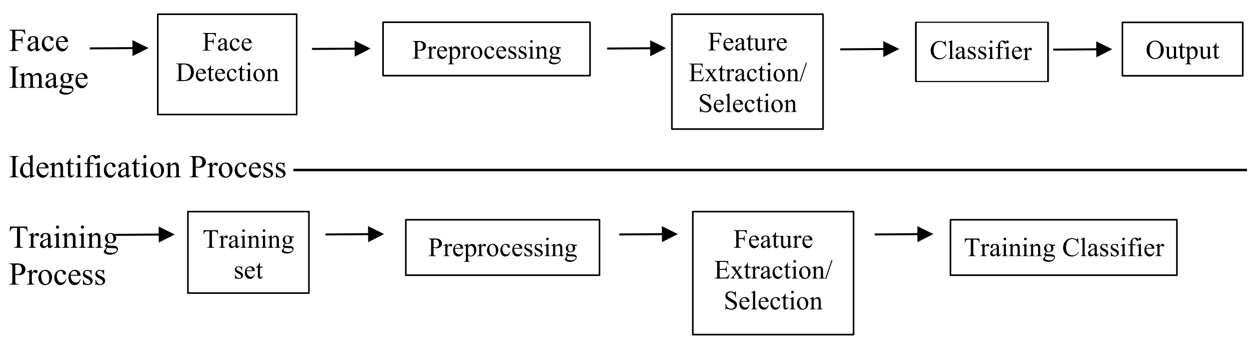

Figure 1. Two-dimensional static face system process

As can be seen from the Figure 1, the face recognition system is a static identification system. The face is recognized by two detection processes and the face can be said to be a three-dimensional figure. The above-mentioned face can be divided into ten modules in total such as face detection module, preprocessing, feature extraction or selection, classifier, output, training set, preprocessing, feature extraction or selection and training classifier. Besides, it mainly detects the face image in the input image. Then, it preprocesses the face image and performs color modification on the face image and supplements the light, etc. Next, the vector features on the face image are extracted by the support vector. The data is then arranged and sorted. Finally, the output is stored in the training set, which is convenient for face recognition training. The face is relatively a high-dimensional mode, which requires considerable data sorting and categorization. The existence of support vector machine has greatly reduced the computational process and computational data. Therefore, support vector machines play an important role in the field of face recognition.

2.1 Image preprocessing

There are many external factors that affect the face image such as reasons for the camera itself and environmental reasons. As an example, firstly is the light factor. The distance between the person and the camera lens, etc., have a great influence on the face image. Therefore, it is necessary to pre-process the face image, such as light supplementation and color adjustment when detecting a face image. Besides, there are three kinds of image preprocessing techniques. The three image preprocessing methods are introduced separately below.

2.2 Histogram equalization

The gray histogram reflects the relationship between each gray level in the image and the frequency at which pixels of the gray level appear, which can be expressed as:

$$\mathrm{his}(n) = \frac{m_n}{M}, n = 1, \ldots, N \quad (1)$$

In the formula (1), n represents the n^{th} gray level, m_n represents the number of pixels of the n^{th} gray scale, M is the number of pixels of the image, and N is the number of gray levels of the image. The main purpose of histogram equalization is to equalize the image information in a small range, and the data information and information features are evenly distributed in the image. In addition, in this small image information, the entropy value and the amount of information contained are the largest. The probability that each part of the image gray level appears in the region is the same, which is called a histogram. After equalization, when the image equalization is completed, and the face image is viewed again, the details of the face image are more obvious as well as a clear display of the content of the face image. The output produced by the histogram equalization operation on the source image f(x, Y) is g(x, y), and the value of g(x, y) can be directly calculated by equations (2) and (3):

$$g(x,y) = N * P(F(x,y) \quad (2)$$

$$P(n) = \frac{1}{M}\sum_{i=1}^{n} \mathrm{his}(i), n = 1, \ldots, N \quad (3)$$

2.3 Size normalization

The face mode is a high-dimensional mode. The size normalized image and the processing method are applied strictly. Plus, the face mode must be the same dimension before the face image can be preprocessed. The face mode can also be called the same size; general size normalized face image preprocessing first need to use bilinear interpolation. Then, through the face image comparison, the final processing, can be done in the following way, set f(x, y) is the interpolated image of the original image g(x, Y), and the pixel g(x, y) corresponds to the pixel $f(x_0, y_0)$ of the original image. The pixel $f(x_0, y_0)$ is located in a grid composed of pixels (x_1, y_1), (x_2, y_1), (x_1, y_2), (x_2, y_2), where $X_2 = x_1 + 1$, $Y_2 = Y_1 + 1$, $x_1 \le x_0 \le x_2$, $y_1 \le y_0 \le y_2$, then the value of $f(x_0, y_0)$) (ie, the value of g(x', y')) can be calculated using bilinear interpolation:

$$f(x_0,y_o) = f(x_0,y_1) + (y_0 - y_1)[f(x_0,y_2) - f(x_0,y_1) \quad (4)$$

Among them,

$$f(x_0,y_1) = f(x_1,y_1) + (x_0 - x_1)[f(x_2,y_1) - f(x_1,y_1)$$

$$f(x_0,y_2) = f(x_1,y_2) + (x_0 - x_1)[f(x_2,y_2) - f(x_1,y_2)$$

2.4 Grayscale normalization

In image grayscale, there are two basic quantities, one is the average quantities and the other is the variance. Gray-scale normalization can also be said to set the values of the mean and variance so that the values remain unchanged. Thus, the facial image feature values can be compared with a fixed mean and variance. This is also called gray-scale normalization. The gray-normalized image pre-processing process can be represented by a matrix or an array. The following is a detailed introduction. If the image with the width M*N is regarded as a matrix or a two-dimensional array whose pixel value is f (x, y), the gray mean and mean square distribution of the image are:

$$u = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) \quad (5)$$

$$\sigma = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) - u} \quad (6)$$

In order to adjust the gray level average quantities and average variance of the image, it is adjusted accordingly to the given values u_0 and σ_0, respectively, the gray value of each pixel of the image is linearly transformed as follows:

$$f(x,y) = \frac{\sigma_0}{\sigma}(f(x,y) - u) + u_0 \quad (7)$$

The gray distribution matrix of the transformed image can be obtained, usually taking parameters: $u_0 = 0, \sigma_0 = 1$.

3 Sample acquisition

In face recognition system, face recognition has a certain probability and the influencing factor is the accuracy of sample acquisition. The appearance of support vector machine can effectively improve the accuracy of the acquisition. Firstly, when the support vector machine takes a sample for face detection, the feature data selected is a pixel value vector. If the eigenvalues are used for data analysis and comparison, the detection process will be lengthened. Therefore, in order to avoid this embarrassing phenomenon, the feature extraction method appears. The support vector machine is used to extract a small number of data sets with obvious features, which is used as the distinguishing vector feature of the face image sample acquisition[1]. Moreover, in the face detection system, there are many methods for obtaining face image samples. Among the more classical feature extraction methods are linear subspace methods such as principal component analysis (PCA) and linear discriminant analysis (LDA).

3.1 Analysis of principal component

The main idea of principal component analysis is to find a projection method that best represents the original data in the mean square sense. It usually uses the eigenvector system of the training sample covariance matrix as the expansion base (ie, the KL coordinate system), and those eigenvectors corresponding to some of the largest eigenvalues are called principal components. After the original sample is linearly projected on these principal components, the resulting projection coefficient is the principal component of the sample. Thus, the original sample can represent the algebraic sum of the product of the principal component and the projection coefficient, which this representation is optimal at the lowest mean square value.

There are N training images $A_k \in R^{m*n}(k = 1,2,...,N)$, and each m*n image matrix A_k is connected in rows to the training sample of mn dimension $x_k(k = 1,2,...,N)$, the average value of all training samples is u, then the overall scatter matrix of the training samples can be expressed as:

$$S_t = \sum_{k=1}^{N}(x_k - u)\,(x_k - u)^T \in R^{m*n} \quad (8)$$

If S_t is used as the production matrix of KL transforming to ∈, ∈ can be expressed as: $\in = xx^T \in R^{mn*mn}$.

Since the dimension mn of the image sample is often much larger than the number N of training samples, the eigenvalues and eigenvectors of ∈ are generally not directly calculated, but the matrix D is constructed first.

$$D = X^T \in R^{m*n} \quad (9)$$

3.2 Linear discriminant analysis

Although the PCA method is the optimal representation of the sample in the least mean square, there is no reason to suggest that the principal component has a significant effect on distinguishing between different categories. The PCA method looks for the direction of the main axis used for effective representation, while the linear discriminant analysis (LDA) method looks for the direction for effective classification. LDA was first proposed by R.A. Fisher in 1936 which is also known as Fisher Linear Discrimination (FLD). Through LDA transformation, not only the dimension of the feature is reduced, but also the sample has good classification characteristics in projection[2].

In the absent of N training images $A_k \in R^{m*n}(k = 1,2,...,N)$, which are classified into class c. The number of samples per class is N_1, and the sample subset of each class is D_1. Each m*n image matrix A_k is connected in rows to a mn-dimensional training sample $x_k(k = 1,2,...,N)$, and the mean of all training samples is u.

$$u = \frac{1}{N}\sum_{i=1}^{1} x_i \quad (10)$$

The mean value of the training samples in class I is $u_i = \frac{1}{N}\sum x$。

3.3 Model selection for multi-class classification

Due to the complexity of face recognition and the high dimensionality of face patterns, this extends the classification method of face recognition. Face recognition can be said to be a multi-class classification, which is also a typical classification case in multi-class classification. Therefore, the classification of face recognition needs to establish different vector classifiers according to different classifications, thereby to solve the problem of multi-class classification of faces. There are two main types of face classification, and the form of the classifier includes one-to-one and one-to-many.

In the one-to-many classification mode, the parameters of the classifier are the same; that is, the parameters are set to a fixed value. Therefore, the recognition elasticity of a one-to-many vector classifier becomes smaller, but it does not affect the promotion of the one-to-many vector classifier mode, but it will have certain influence in the training set as well as may have the effect of not satisfactory in the training set[3].

Secondly, it is well understood in the one-to-one classification mode that all the parameters used by the vector classifier are set according to their own needs. In other words, it can be said that it is the same method as centralized tutoring. Plus, because the number of one-to-one vector classifiers is limited, there are relatively few samples that can be stored. Thus, the main role is to make bug fixes and focus issues.

4 Prospects for follow-up

(1) The boundary features of the support vector are obvious due to the main reason that the support vector presents the geometric distribution. The geometric pattern distribution type is more conducive to the recognition of the face image. Then, for the quadratic programming problem in face recognition, it can be solved by the geometric method.

(2) Whether there is a feature space to construct the Delaunay triangulation network, the input space seeks the boundary set to be transformed into the high-dimensional feature space and avoids the "dimensionality disaster" problem in the Delaunay triangulation network in the input space[4].

(3) In face recognition, the extraction of support vector features is complementary and cannot be completely isolated. The basis of the selection and training of these vectors is based on the geometric method, and the relationship between them is complex.

(4) The focus of future machine learning research can be said to solve the problem between data collection and space. Since the consistency assumptions between these two parameters are different, it is necessary to solve this problem by promoting and researching machine learning capabilities.

5 Conclusion

As a conclusion in practical applications, machine learning based on support vector machine is scientific, advanced and adaptable, and satisfactory classification results can be obtained. A personal credit assessment model based on support vector machines can indeed help banks or lenders make the right decisions. Lastly, the model still has a broad space for improvement. Learning more advanced theoretical knowledge to complete the upgrade of the model is the next step in the effort.

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