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REVIEW

Twin Support Vector Machine: A review from 2007 to 2014

Divya Tomar *, **Sonali Agarwal**

Indian Institute of Information Technology, Allahabad, Uttar Pradesh, India

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Abstract Twin Support Vector Machine (TWSVM) is an emerging machine learning method suitable for both classification and regression problems. It utilizes the concept of Generalized Eigenvalues Proximal Support Vector Machine (GEPSVM) and finds two non-parallel planes for each class by solving a pair of Quadratic Programming Problems. It enhances the computational speed as compared to the traditional Support Vector Machine (SVM). TWSVM was initially constructed to solve binary classification problems; later researchers successfully extended it for multi-class problem domain. TWSVM always gives promising empirical results, due to which it has many attractive features which enhance its applicability. This paper presents the research development of TWSVM in recent years. This study is divided into two main broad categories - variant based and multi-class based TWSVM methods. The paper primarily discusses the basic concept of TWSVM and highlights its applications in recent years. A comparative analysis of various research contributions based on TWSVM is also presented. This is helpful for researchers to effectively utilize the TWSVM as an emergent research methodology and encourage them to work further in the performance enhancement of TWSVM.

Contents

* Corresponding author.
E-mail addresses: divyatomar26@gmail.com (D. Tomar), sonali@iiita.ac.in (S. Agarwal).

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1. Introduction

The formulation of SVM is proposed by Vapnik et al. in 1990s which is based on statistical learning theory [1,2]. Initially, SVM was developed to solve the two-class classification problem but later it was formulated and extended to solve multiclass classification problems [3–9]. SVM divides the data samples of two classes by determining a hyper-plane in input space that maximizes the separation between them. SVM also works effectively for the categorization of data samples which are not classified linearly by utilizing the theory of kernel function [10]. Several kernel functions for example Gaussian, Polynomial, Sigmoid, etc. are available which are used to transform data samples into a higher dimensional feature space. Then SVM determines a hyper-plane in this space and divides the data samples of different classes [10–12]. Fig. 1 shows the classification by SVM with the help of kernel function into two class labels.

SVM has numerous advantages such as it provides global solution for data classification. It generates a unique global hyper-plane to separate the data samples of different classes rather than local boundaries as compared to other existing data classification approaches. Since SVM follows the Structural Risk Minimization (SRM) principle, it reduces the occurrence of risk during the training phase as well as enhances its generalization capability. Due to its better performance, SVM is one of the most widely used classification techniques of data mining that has applications in many fields ranging from disease detection, text categorization, software defect prediction, speech recognition, face identification, bankruptcy prediction, intrusion detection, time series forecasting, music emotion detection, etc. [13–38]. But one of the main issues with the conventional SVM is to obtain the solution of a complex Quadratic Programming Problem (QPP).

Recently, Mangasarian et al. introduced a Generalized Eigen-value Proximal SVM (GEPSVM) which generates two non-parallel hyper-planes for two class problems [39]. In this approach, the patterns or data samples of each class lie in the close proximity of one hyper-plane and maintain clear separation with other. On the basis of SVM and GEPSVM, Jayadeva et al. proposed a novel binary classifier, Twin Support Vector Machine (TWSVM), which classifies the patterns of two classes by using two non-parallel hyper-planes [40]. TWSVM solves a pair of QPPs instead of single complex QPP as in traditional SVM. In SVM, all data samples provide constraint to QPP i.e., SVM dual formulation is depending on the number of all data samples in the training set. While in TWSVM, patterns of one class provide constraints to other QPP and vice versa.

For 'n' size training data samples the computational complexity of SVM is $O(n^3)$. If number of data samples in each class is approximately equal to $n/2$, then the complexity of TWSVM is $O(2 \times (n/2)^3)$ which is four times faster than that of traditional SVM. Ratio of computational complexity of SVM and TWSVM is