Abstract

Motivation and Objective: In recent years support vector machine (SVM) has emerged as a powerful learning approach and successfully be applied in a wide variety of applications. However, SVM is considered slower than other learning approaches in both testing and training phases. In testing phase SVMs have to compare the test pattern with every support vectors included in their solutions. To reduce this computational expense, reduced set methods try to replace original SVM solution by a simplified one which consists of much fewer number of vectors, called reduced vectors. However, the main drawback of former reduced set methods lies in the construction of each new reduced vector: it is required to minimize a multivariate function with local minima. Our first objective was aiming at building a better reduced set method which overcomes the mentioned local minima problem. The second objective was to find a simple and effective way to reduce the training time in a model selection process. This objective was motivated by the fact that the selection of a good SVM for a specific application is a very time consuming task. It generally demands a series of very expensive SVM training with different parameter settings.

Methodology: Starting from a mechanical point of view, we proposed to simplify support vector solutions by iteratively replacing two support vectors with a newly created vector, or to substitute two member forces in an equilibrium system by an equivalent force. This approach possess a big advantage that the computation of the new vector involves only two support vectors being replaced, not to involve all vectors as in the former top-down approach. The extra task of the bottom-up method is to find a heuristic to select a good pair of support vectors to substitute in each iteration. This heuristic aims at minimizing the difference between the original solution and the simplified one. Also, it is necessary to design a stopping condition to terminate the simplification process before the possible loss in generalization performance can get out of control. For the second problem, our intensive investigation reconfirmed that different SVMs trained by different parameter settings share a big portion of common support vectors. This observation suggests a simple technique to use the results of previously trained SVMs to initialize the search in training a new machine. In a general decomposition framework for SVM training, this better initialization makes optimization process converges more quickly.

Finding and Conclusion: The bottom-up approach leads to a conceptually simpler and computationally less expensive method for simplifying SVM solutions. We found that it is reasonable to select a close support vector pair to replace with a newly constructed vector, and this construction only requires finding the unique maximum point of a univariate function. The uniqueness of solution does not only make the algorithm run faster, but it also makes the reduced set method easier to use in practice. SVM users do not have to run many trials and wonder about different results returned in different runs. Experimental results on real life datasets shown that our proposed method can reduce a large number of support vectors and keeps generalization performance unchanged. For the second problem, experiments on various real life datasets showed that by initializing the first working set using the result of trained SVMs, the training time for each subsequent SVM could be reduced by 22.8-85.5%.