One-Class SVM in Multi-task Learning

Xiyan He, Gilles Mourot, Didier Maquin & José Ragot
Centre de Recherche en Automatique de Nancy, CNRS UMR 7039 - Université Henri Poincaré, Nancy-I
2, avenue de la forêt de Haye, 54500 Vandœuvre-lès-Nancy, France

Pierre Beauseroy & André Smolarz
Institut Charles Delaunay, STMR CNRS UMR 6279 - Université de Technologie de Troyes
12, Rue Marie Curie, BP 2060, F-10010 Troyes, France

ABSTRACT

Classical machine learning technologies have achieved much success in the learning of a single task at a time. However, in many practical applications we may need to learn a number of related tasks or to rebuild the model from new data, for example, in the problem of fault detection and diagnosis of a system that contains a set of equipments *a priori* identical but working under different conditions. Indeed, it is common to encounter in industrial problems a number of *a priori* identical plants, such as in the building or maintenance of a fleet of nuclear power plants or of a fleet of their components. In such cases, the learning of the behavior of each equipment can be considered as a single task, and it would be nice to transfer or leverage the useful information between related tasks. Therefore, Multi-Task Learning (MTL) has become an active research topic in recent years.

While most machine learning methods focus on the learning of tasks independently, multi-task learning aims to improve the generalization performance by training multiple related tasks simultaneously. The main idea is to share what is learned from different tasks (*e.g.*, a common representation space or some model parameters that are close to each other), while tasks are trained in parallel [1]. Previous works have shown empirically as well as theoretically that the multi-task learning framework can lead to more intelligent learning models with a better performance.

In this paper, we present a new approach to multi-task learning based on one-class Support Vector Machines (one-class SVM). The one-class SVM proposed by Schlkopf et al. [2] is a typical method for the problem of novelty or outlier detection, also known as the one-class classification problem due to the fact that we do not have sufficient knowledge about the outlier class. For example, in the application of fault detection and diagnosis, it is very difficult to collect samples corresponding to all the abnormal behaviors of the system. In the literature, this type of problem can be treated as a two-class classification problem, where the first class is called target class whose samples are available and the second class is called outlier class whose samples are often difficult to obtain. The main advantage of one-class SVM over other one-class classification methods is that it focuses only on the estimation of a bounded area for samples from the target class rather than on the estimation of the probability density. The bounded area estimation is achieved by separating the target samples (in a higher-dimensional feature space for non-linearly separable cases) from the origin by a maximum-margin hyperplane which is as far away from the origin as possible.

Inspired by the work of Evgeniou and Pontil [3], we introduce the one-class SVM method, a widely used tool for single task learning, into the framework of multi-task learning. In the proposed method, we first make the same assumption as in [3], that is, the model parameters of different tasks are close to a certain mean function. This assumption is reasonable due to the observation that when the tasks are similar to each other, usually their model parameters are close enough. Then, a number of one-class SVMs, one for each task, are learned simultaneously. Our multi-task approach is easy to implement since it only requires a simple modification of the optimization problem in the single one-class SVM. Experimental results demonstrate the effectiveness of the proposed approach.

REFERENCES

[1] Caruana, R., 1997. Multitask Learning. Machine Learning, 28(1), 41-75.

[2] Schölkopf,B. and Platt, J.C. and Shawe-Taylor,J. and Smola, A.J. and Williamson, R.C., 2001. Estimating the support of a high-dimensional distribution. Neural Computation, 13(7), 1443-1471.

[3] Evgeniou, T. and Pontil, M., 2004. Regularized multi-task learning. Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA, 109-117.