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# ABT-SVDD: A method for uncertainty handling in domain adaptation using belief function theory

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ABSTRACT

Domain adaptation involves adapting a model trained on one domain to work effectively on another, which can have different statistical properties, such as distributions, correlations, and relationships between features. These heterogeneities can lead to uncertainty, impacting the model's performance. Despite many studies that have been done on domain adaptation, most have ignored the adverse impact of uncertain and noisy data on adaptation and classification. To address this issue, the proposed method, Adaptive Belief-based Twin Support Vector Data Description (ABT-SVDD), extends the one-class support vector data description (SVDD) to an adaptive twin classifier and integrates it with a belief-based sample weighting approach. Also, it utilizes a combination of Hermite polynomial and Gaussian kernels to enhance the computational power of the linear objective function of the SVDD classifier while improving the generalization capability. The effectiveness of ABT-SVDD has been compared to the state-of-the-art methods on several tasks taken from two benchmark datasets. The experimental results demonstrate that ABT-SVDD significantly improves classification accuracy on various tasks with varying amounts of labeled data in the target domain. Specifically, in normal situations, ABT-SVDD outperforms competing methods by 6.33% to 9.08%, while in noisy situations, it achieves a more significant improvement of 9.87% compared to the competing methods. Besides, the Wilcoxon statistical test demonstrates the superiority of ABT-SVDD over state-of-the-art ones in terms of classification accuracy and computational time.



## 1. Introduction

Traditional machine learning methods have proven to be successful in various tasks. Nonetheless, much of the success has come at the price of excessive human effort in manual data labeling. Transfer learning (TL) is an alternative approach to traditional machine learning methods that can reduce the need for manual data labeling by leveraging the knowledge obtained from related domains to improve the model's performance on new, unseen data. This approach is beneficial in scenarios where labeled data is scarce or difficult to obtain, such as clinical research, *recommendation systems, the defense industry*, etc. [1–5].

There are two main types of TL: homogeneous and heterogeneous. The former considers the source and target domains to have similar, same-dimensionality feature spaces. In contrast, different feature spaces exist for the latter [6]. From another point of view, TL methods can be categorized into three main approaches, including inductive TL, unsupervised TL, and transductive TL [7,8].

Inductive transfer learning aims to transfer knowledge from a source domain to a target task in a new target domain where the data distribution may differ from the source domain. This approach can be further categorized into two groups based on the availability of labeled data in the source domain. The first group, supervised inductive TL, assumes that a lot of labeled data is available in the source domain that can be used to train a model, and the knowledge learned from this task can be transferred to the target task. The second group, unsupervised inductive TL, assumes that no labeled data is available in the source domain, and the knowledge is transferred from the source domain to the target domain using unsupervised learning techniques.

Unsupervised transfer learning focuses on leveraging the unlabeled data from the source domain to extract useful information that can improve the performance of the target task. In unsupervised transfer learning, the model is trained on the unlabeled data from the source domain to learn a generic representation or structure that captures the underlying patterns and relationships in the data. This learned representation is then transferred to the target task, which can be fine-tuned or combined with labeled data from the target domain to improve performance.

Transductive transfer learning is typically used when both the source and target data are available during training. Still, the

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