DOMAIN ADAPTATION USING KERNEL OR MANIFOLD ALIGNMENT FOR OBJECT CATEGORIZATION

Input: Training images of different object categories from source domain.

Output: Class label of test images obtained from target domain.

Dataset: Office+Caltech Dataset [2] containing 10 classes of objects on 4 domains (Amazon, Caltech, Dslr and Webcam)

Problem description [1]:

Domain Adaptation deals with the problem when the training and the testing samples, in a classification task, follows different distribution. The training instances are sampled from SOURCE domain while the testing samples are drawn from the TARGET domain.

This is a problem of supervised domain adaptation [1], where a few labeled training samples are available from the target domain. We use these training samples, along with the labeled training samples obtained from the source domain for domain adaptation. A weighted composite kernel is calculated from several base kernels which is to be aligned with the outer product of observed class labels of the training samples. The aim of the algorithm is to find the optimal weight vector used for calculating weighted composite kernel, such that the best kernel alignment is achieved. Once we calculate the desired weighted composite kernel, we can use it to train a classifier which will give improved classification accuracy on test samples from target domain.

Domain Adaptation using manifold alignment [2, 3] deals with finding a suitable lower dimensional sub-space such that the underlying geometry of the source and target domains are aligned or made similar to each other. The local geometry of the instances from two domains are preserved separately while doing the transformation. The correspondence between the two domains are to be found out for doing the correct transformation of data. The classifier trained with the transformed source domain samples will give better result when tested with the transformed target domain samples.

Analysis of results:

Results are to be analyzed using measures like classification accuracy and precision/recall/F measures.

Comparative study with naïve combination and source-only and target-only methods are to be shown. Bonus marks are awarded for any new/modified functions used for estimating kernel for transformed source domain.

Reference:

1. A. Howard and T. Jebara. "Transformation Learning Via Kernel Alignment". International Conference on Machine Learning and Applications (ICMLA), 2009.

2. Chang Wang, S Mahadevan, “Heterogeneous domain adaptation using manifold alignment”, International joint conference on Artificial Intelligence (IJCAI), 2011.
3. Chang Wang and Sridhar Mahadevan , “Manifold Alignment Preserving Global Geometry”, International Joint Conference on Artificial Intelligence (IJCAI 2013),

Additional reference:

1. R. Gopalan, R. Li, V. M. Patel and R. Chellappa, "Domain adaptation for visual recognition," under revision, IJCV, 2015.
2. K. Saenko, B. Kulis, M. Fritz and T. Darrell, "Adapting Visual Category Models to New Domains" In Proc. ECCV, September 2010