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Flexible Domain Adaptation for Multimedia Indexing

Emilie Morvant, Amaury Habrard, Stéphane Ayache
{emilie.morvant,amaury.habrard,stephane.ayache}@lif.univ-mrs.fr

INTRODUCTION, NOTATIONS AND MOTIVATION

We consider binary classification task:
- \( X \) input space, \( Y = \{-1, 1\} \) label set
- \( P_S \) source domain: distribution over \( X \times Y \)
- \( P_D \) target domain: different distribution over \( X \times Y \)
- \( h \) hypothesis
- \( h \) error of a hypothesis
- \( \nu \) supervised classification objective
- \( \nu \) target domain: different distribution over \( X \times Y \)
- \( \nu \) errors of a hypothesis

For example:
- We have labeled images from a Web image corpus, i.e., \( P_S \)
- Is there a Person in unlabeled images from a Video corpus, i.e., \( P_D \) ?

\( \nu \) The Learning distribution is different from the Testing distribution
\( \nu \) How can we learn, from the source domain, a low-error classifier on the target domain?

DOMAIN ADAPTATION

Theorem 1 ([2]). Let \( H \) an hypothesis space. If \( D_S \) and \( D_T \) are respectively the marginal distributions of source and target instances, then for all \( \delta \in [0,1] \), with probability at least \( 1 - \delta \), for every \( h \in H \):

\[
\nu(h) \leq \epsilon(h) + \frac{1}{2} d_{TV}(D_S, D_T) + \nu,
\]

where \( d_{TV}(D_S, D_T) \) is the TV-distance between \( D_S \) and \( D_T \).

\( \nu \) The domination of distance helps to build a new projection space to move closer the domains.

DOMAIN ADAPTATION OF LINEAR CLASSIFIERS BASED ON GOOD SIMILARITY FUNCTIONS

Divergence: Iteration

Experimental Setup
- Similarity function: Gaussian kernel \( K(x, x') = \exp(-\|x - x'\|^2 / 2\sigma^2) \)
- Reverse Validation (together with a Gaussian kernel)
- Toy problem “into-swimming moons”
- \( P_S \): \( 8 \times 8 \) according to 8 rotations
- \( P_D \): \( 8 \times 8 \) according to 8 rotations
- Toy problem: Percepts
- Image Indexing: PascalVOC’07
- \( P_S \): PascalVOC’07 train \( \sim 1/3 \)
- \( P_T \): PascalVOC’07 Test \( \sim 1/3 \)

REFERENCES