Unsupervised Domain Adaptation

Two domains: Source domain with labeled samples and Target domain with unlabeled samples. Goal: construct target-domain specific predictive function by leveraging the knowledge from the source domain.

Why?
- Distribution Shift: Data distribution can change between different domains (i.e., datasets, features, modalities, ...).
- Dataset Bias: Different bias in different domain.
- About 20% drop in performance when models trained on one domain are directly applied to another.
- Finite collection of images can rarely capture vast variations present in real-world data. Hence, ‘combine’ data across domains.

Contribution
- New probabilistic domain adaptation model to construct a common subspace for source-target classification.
- Joint learning of subspace & classification functions.
- Automatic inference of dimensionality of the shared latent space.
- Novel regularized Variational Bayes (VB) algorithm for efficient estimation of model parameters.
- Method to leverage unlabeled data from target domain through minimum uncertainty classifier design.

PUnDA

Jointly learn mappings \( \Phi \) and \( \Phi' \) from domain-specific features \( x \) and \( x' \) to matched subspaces \( s \) and \( s' \), automatically infer subspace dimension, and cross-domain classifier \( W \). Rely on pre-trained feature extractors.

Inference

Variational Bayes (VB) algorithm to approximate posterior distribution of latent variables \( \Omega = \{ S, S', W, \Phi, \Phi', Z, \Pi, \gamma, \tau \} \):

\[
q'(\Omega) = \operatorname{arg\ max}_q \mathbb{E}_q[\log P(X, Y, S, \Omega)] + H[q(\Omega)] - \lambda L(S, S') + \lambda' L'(S', W, Z),
\]

Cross-Domain Regularizer
Probabilistic MMD using Blattacharya kernel to measure the posterior similarity accounting for uncertainty of projections:

\[
L(S, S') = \sum_{i,j} K(s_i, s_j) / M - 2 \sum_{i,j} K(s_i, s'_j) / M + \sum_{i,j} K(s'_i, s'_j) / M
\]

\[
K(q(s), q(s')) = \log \left( \int q(s)q(s') \log \frac{q(s)}{q(s')^2} ds \right).
\]

Target Domain Regularizer
Minimize uncertainty of target classifier / Shannon entropy:

\[
L'(W, S', Z) = \frac{M}{M-1} \sum_{j=1}^{M} \log P(y_j = c).
\]

Evaluation: Datasets & Main Results

Office: 10 classes, VGG/SURF features

Multi-PIE: 67 classes, grayscale intensity features

Classification Accuracy

References


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Shared Space Embedding

Fig.: First row: Original features (red points: source sample, blue points: target samples). Second row: PUnDA features.

Learned Shared Space Dimension

Fig.: \( E[q'(Z)] \) for Office+Caltech10 and Multi-PIE.