Transfer Neural Trees for Heterogeneous Domain Adaptation

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Introduction

- Domain adaptation:
  Address the same learning task across different domains
- Heterogeneous domain adaptation:
  Source and target-domain data are described by distinct types of features.

Related Works

- Map cross-domain data onto a common subspace for classification
- Jointly learning of mapping & classification functions from cross-domain labeled data [1]
- Project cross-domain data for suppressing domain differences [2]
- A pair of DNNs with shared parameters for matching cross-domain data. [3]

Proposed Method

- Transfer Neural Trees (TNT)
  - Source-domain mapping \( f_S \)
  - Target-domain mapping \( f_T \)
  - Prediction layer \( G \)

  \[ D_S = [X_S, Y_S] \text{: Labeled source-domain data} \]
  \[ D_T = [X_T, Y_T] \text{: Labeled target-domain data} \]
  \[ D_U = [X_U, Y_U] \text{: Unlabeled target-domain data} \]

- Learning \( f_S \) and \( G \):
  - Minimize prediction loss \( L_p \) of source-domain data \( X_S \)
  \[ \min_{f_S, G} \sum_{(x,y) \in D_S} L_p(f_S(x), y) + \lambda \sum_{(x,y) \in D_U} L_p(f_S(x), y) \]

- Learning \( f_T \) with fixed \( G \) (semi-supervised learning):
  - Minimize prediction loss \( L_p \) of target-domain labeled data \( X_L \)
  - Minimize embedding loss \( L_e \) of target-domain labeled & unlabeled data
  \[ \min_{f_T} \sum_{(x,y) \in D_T} L_e(f_T(x), y) + \lambda \sum_{(x,y) \in D_U} L_e(f_T(x), y) \]

  - \( L_p(f_S(x), y) = -log \left( \frac{P(y|x)}{P(y|x)} \right) \)
  - \( L_e(f_T(x), y) = -log \left( \frac{P(y|x)}{P(y|x)} \right) \)

  - Increase prediction consistency \( \rightarrow \) preserve structural consistency btw \( X_L \) & \( X_U \)

Experiments

- Datasets
  - Object recognition (10 classes):
    - Amazon: 959 DeCAF/SURF features
    - Webcam: 296 DeCAF/SURF features
    - Caltech: 1124 DeCAF/SURF features
  - Text-to-image recognition (8 classes):
    - NUS-WIDE tag data: 800 NN features
    - ImageNet: 800 DeCAF features

- Settings
  - Source domain: all data in dataset as \( X_S \)
  - Target domain: 3 per class as \( X_U \), the rest as \( X_U \)

Evaluation

- Cross Features
  - Cross Datasets (b: DeCAF > t: SURF)
  - Cross Datasets (b: NIM > t: DeCAF)
  - Cross Datasets (b: NIM > t: DeCAF image)
  - Cross Modalities (b: NIM/tag > t: DeCAF/IMAGE)

- Evaluation
  - Cross Features
  - Cross Datasets
  - Cross Modalities

Visualizations

- Different \( G \) in TNT

Conclusions

- TNT for semi-supervised & cross-domain deep learning
- Transfer-NDF with stochastic pruning for HDA
- Embedding loss in TNT for preserving prediction & structural consistency
- Promising results on cross-feature, domain, and modality classification tasks

Reference