Paper review
Universal Domain Adaptation through Self-Supervision

Motivation

The Domain Adaptative Neighborhood Clustering via Entropy optimization (DANCE) is a model inspired from various models which were designed to tackle specific cases of like Closed-set (CDA) , Partial (PDA) , Open set domain adaptation (ODA) however there wasn't a single model which could tackle all cases together which happens if we don't the classes of target domain before hand. Another issue that this model fixed is the over-reliance on source supervision since the other models focussed on aligning target features with source, rather than on exploiting structure specific to the target domain.

Novelties

Task in hand is to do universal domain adaptation given a labeled source domain and an unlabeled target domain for this the authors have provided two loss functions that can be used :

1) Neighborhood Clustering Loss : The objective is to move each target point either to a "known" class in the source or to its neighbor in the target. If "unknown" samples have similar characteristics with other "unknown" samples, then this clustering objective will help us extract discriminative features. The advantage of the design is there is no need to specify the number of clusters in the target domain.
2) Entropy Separation Loss : Using this, the authors propose to draw a boundary between "known" and "unknown" points using the entropy of a classifier's output. They expect that the entropy of "unknown" target samples will be larger than threshold whereas for the "known" ones it will be smaller. However, in many cases, the threshold can be ambiguous and can change due to domain shift. Therefore a confidence threshold "m" is introduced which allows to give the separation loss only to confident samples.

In the end, authors propose training with domain specific batch normalization to enhance alignment between source and target domain. The batch normalization layer whitens the feature activations, which contributes to a performance gain. Simply splitting source and target samples into different mini-batches and forwarding them separately helps alignment, this weak alignment matches the goal of this paper because strongly aligning feature distributions can harm the performance on non- CDA problems. After this the combined loss function is minimized which is formed after combining the usual cross entropy loss with the above 2 losses.

Major contributions

The results obtained from the paper are compared with the state of the art results on 3 datasets i.e. Office, OfficeHome and VisDA along with the models that were designed specifically for these datasets knowing the target domain. DANCE has outperformed all models for OfficeHome dataset however it has a slightly lesser poor performance than the algorithms designed specifically for the purpose which was expected since the model is generalizing for all cases without knowing the target.

Critical analysis

The negative impacts of this model include misuse for criminal activities, vulnerability to adversarial attacks, lack of interpretability, and potential negative transfer. Caution is also advised by authors for mission-critical applications or decisions without human oversight.