1 Summary

Tradition DA methods are based on the idea of finding shared representations and ignore the individual characteristics of each domain. The paper proposes a method of unsupervised DA by partitioning feature level subspace of an image into two orthogonal subspaces: private subspace captures domain specific representations whereas common subspace captures domain invariant representations. Learning domain invariant features in common subspace is achieved either using adversarial method or MMD loss. Reconstruction loss is enforced for regularization. Experiments are run on 5 different tasks and its observed that the model beats state of the art in all tasks.

2 Strengths

- The idea of explicitly modeling private and shared components of domain representations is novel. This allows DSN to not only perform the task we care about in the source domain, but also to use the partitioned representation to reconstruct the images from both domains.
- Using scale-invariant mean square error reconstruction loss instead of traditional mean square error is clever. Traditional MSE penalizes predictions that are correct up to a scaling term. Hence, even with two exactly similar images but different brightness, it would fixate high loss value which is suboptimal.

3 Weaknesses

- It seems network topology has to be re-designed for each specific domain adaptation task. Previous approaches used same model topology for DA tasks and it might be possible that this method is highly sensitive to architecture.
- Authors have used a small labeled target data. So in a sense, this is not entirely unsupervised domain adaptation task.

4 Critique of Experiments

- Authors have considered 5 different domain adaptation tasks. 3 tasks for digit adaptation, Synth Sign to GTSRB and Synth Object to LINEMOD. Results reveal that DSN outperforms all state of the art methods on all 5 tasks. Image reconstructions from shared-only, private-only and combined subspace representations truthfully follow intuitive logic. For MNIST -¿ MNIST-M, complete information is stored in common subspace for MNIST data while its private subspace contains noise. This makes sense because MNIST is a sub-domain of MNIST-M with the only differences in background color.
- As ablation study, removing soft orthogonality constraint reveals that accuracy drops by approximately 2%. Replacing the scale–invariant MSE with regular MSE also decreases the average accuracy by similar numbers.
- Using DANN based adversarial loss instead of MMD loss results in a higher accuracy. This is consistent with results obtained for domain adaptation using MMD regularization and DANN alone.

5 Follow Ups/Extensions

- Authors argue that since Office dataset exhibits significant variations in both low-level and high-level parameter distributions, they did not publish results on the dataset. However it is a standard evaluation setup within the adaptation community so without that comparison it is difficult to place this algorithm is proper context. It would be interesting to see model performance on it.
- DA performance on 3D objects dataset would be interesting to see since the task of finding orthogonal subspace would be a lot more difficult in that dataset. Since the model is very large, study of robustness to hyperparameters is very critical.