CSE 291 A00
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1 Title:
Domain Separation Networks

2 Summary:
This paper proposes to partition hidden representation of images into domain specific and domain invariant components. Soft orthogonality constraints ensure that the sub-spaces of the two components are orthogonal while reconstruction loss ensures meaningful information is captured. Further, to ensure domain invariant component is the same across source and target domains, the authors propose similarity constraints achieved using adversarial mechanism/MMD. Downstream domain adaptation task is trained on this invariant component. SOTA results presented on classification on Digits datasets, GTSRB, and pose estimation on LineMod show the effectiveness of the approach.

3 Strengths:
i) Orthogonality, similarity and reconstruction losses work in conjunction to ensure that low-level domain specific information from the image goes to private sub-space and high-level information is retained in the shared sub-space. Domain adaptation using only high level features is easier. ii) The concept of domain separation and DSN algorithm is generic and can be extended to a variety of vision and learning tasks. iii) Similarity loss is scalable to newer algorithms, any distribution matching technique can be applied to the DSN algorithm, as demonstrated in the paper using DANN, MMD. iv) Gradient reversal layer improves the ease-of-use of adversarial training strategies and applicable to many mini-max settings.

4 Weaknesses:
i) Downstream task may suffer from the absence of low-level information in the invariant embedding. ii) The usage of shared decoder across domains for the reconstruction loss is not clearly justified. Since the private sub-spaces are different, there is simply no reason to share the decoder weights across domains. iii) Since the embedding depends heavily on reconstruction, if the reconstruction is improper, say in diverse datasets with not enough samples, the whole mechanism breaks down. iv) Utilizes target labels for hyper-parameter tuning violating unsupervised domain adaptation assumption.

5 Analysis of Experiments:
i) DSN with MMD is worse as compared to DSN with DANN showing the effectiveness of adversarial approaches, while adding DSN in each case improves upon the results over baseline. ii) SOTA results on digits datasets, Synthetic to LineMod domain adaptation for pose estimation and Synthetic traffic signs to GTSRB demonstrates the effectiveness of the algorithm. iii) Scale invariant reconstruction is shown to be better than simple $L2$ in Table 3. iv) Although, interpretability is claimed, Figure 4. shows it's not very easy to interpret.

6 Possible Extensions:
i) Not sharing the decoder might improve the results by allowing reconstructions for diverse source and target domains. Orthogonality and similarity should still work. ii) Achieve domain separation in CycleGAN/CoGAN by having similar embedding space as DSN. This will achieve pixel level domain transfer and also makes sure the high level information is shared properly across domains through the orthogonality and similarity constraints.