CSE 291 A00
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1 Title:

Deep Domain Adaptation by Geodesic Distance Minimization

2 Summary:

This paper proposes to align the covariances of activations across source and target domains by minimizing their Riemannian distance. When coupled with task-specific loss on source domain and first order moments alignment, this paper achieves improved performance over Euclidean distance based covariance alignment on Office-31 dataset.

3 Strengths:

i) The motivation to use Riemannian distance is theoretically justified as the covariance matrices are PSD and hence, lie on Riemannian manifold. This is in contrast to using simple Euclidean distances.
ii) Empirically, improved performance over Euclidean covariance alignment and further improvement upon adding mean loss is shown. This validates the basic claims of the paper.

4 Weaknesses:

i) Inadequate experimentation as the results are shown only on one architecture and one dataset. This raises questions on generalizability and scaling of the proposed method.
ii) Comparison with other distribution alignment methods such as kernel methods like JAN, DAN are not presented. Since these methods align distributions in RKHS, theoretically they match all the moments. So, a comparison ought to have been given.
iii) Performance improvement is demonstrated against one baseline which is also not very strong. It is unclear how this method interacts with adversarial alignment used by SOTA methods when this term is added to them.
iv) Qualitative results on domain alignment such as T-SNE and A-Score are not presented
v) Back-propagating through eigen values can lead to numerical issues

5 Analysis of Experiments:

i) Improved results (72.87%) are presented over CORAL (71.77%) on Office-31 dataset. Without first order moment matching, (72.48%) accuracy is reported validating the claims
ii) Figure 4. experimentally verifies that the correlation between the two loss terms (mean and covariance alignment) isn't very strong and hence justifies the usage of both simultaneously.

6 Possible Extensions:

i) Aligning the covariance of joint distribution over many layers similar to JAN. Aligning the covariance of joint distribution over input and output distribution, similar to joint optimal transport.
ii) Experimenting the interactions with implicit distribution matching techniques such as adversarial alignment, whether this offers any additional benefit