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1 Title:
AutoDIAL: Automatic Domain Alignment Layers

2 Summary:
This paper adopts same philosophy as Adaptive Batch Normalization (AdaBN) technique where different models are learned for source and target domains where the difference is imposed only by batch norm statistics. But this paper proposes to learn the degree of alignment at each layer by learning additional parameter α, that controls mixing of batch norm statistics through proxy distribution. Additionally, a maximal entropy prior is imposed on network parameters based on target data. Positive experimental results are demonstrated on Office-31, Office-Caltech and Caltech-ImageNet with AlexNet and Inception architectures.

3 Strengths:
i) Target data is utilized at training stage, as opposed to AdaBN, and this can help in generalizing to a target classifier.
ii) Learns the degree of domain alignment automatically which is a novel contribution. The network can decide which layers to adapt and by how much.
iii) Entropy prior can lead to low levels of class overlap and hence, positively influence domain alignment and target prediction
iv) Achieved SOTA on Caltech-ImageNet, Office-31 and Office-Caltech
v) Simple to train and implement. Easily applicable to Conv Layers, LSTM layers etc.

4 Weaknesses:
i) Not applicable when there are multiple source and target domains
ii) Only the first and second order statistics are aligned.
iii) Joint distribution of input and labels and joint distribution across multiple input layers are not taken into account
iv) Explainability of the model reduces. For example, it's unclear why almost all layers of inception net are adapted in Figure 3b. and goes against common intuition of domain specific initial layers to domain invariant final layers.

5 Analysis of Experiments:
i) Table 2. shows huge improvement over AdaBN (82.2% vs 76.7%) on Office-31 dataset, validating the improvement over AdaBN.
ii) Table 1.,2.,4.,5. suggest SOTA results on multiple datasets and architectures.
iii) Degree of domain alignment on AlexNet follows the intuition that initial layers are domain specific and require more alignment and vice-versa. However, such inference breaks down in case of Inception architecture (Figure 3b.)
iv) JAN performs better in some of the difficult tasks suggesting a label shift.

6 Possible Extensions:
i) Looking at joint distribution across layers and trying to align them through similar, albeit cross layer, proxy distribution and corresponding statistics.
ii) Extending degree of domain alignment to multiple source and target domains by, possibly, a convex combination of distributions and corresponding statistics.
iii) Experiment domain adaptation on RNN and CNN layers using this approach