MA Thesis: Learn to Adapt under Domain Shifts and Class Mismatch

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Abstract:
Employing the correct domain adaptation (DA) techniques is a cornerstone for the adoption of transferable models. DA ensures that a model trained on data from a source domain S would perform well on data from a target domain T. This could be achieved either in a supervised or unsupervised fashion depending on the labels availability in domain T. When the labels of T are different from S, the task is referred to as open set domain adaptation. It has been seen that learning a disentangled feature representation produces a more abstract and transferable representation. In this thesis, we aim to explore the efficacy of disentangled representations in unsupervised open set domain adaptation. This is important in medical application where labeling data is costly and time consuming. Hence, using labeled data from a source domain then adapting the model on larger amounts of unlabeled target domain data is highly appreciated. The unlabeled data could be collected for a different task which may lead to label mismatch with the labeled data. Therefore, we study the problem in open set settings. This will be first tested on computer vision datasets such as (MNIST, USPS, SVHN) and (Amazon, DSLR, Webcam, Caltech-256), then on a medical dataset, if possible.

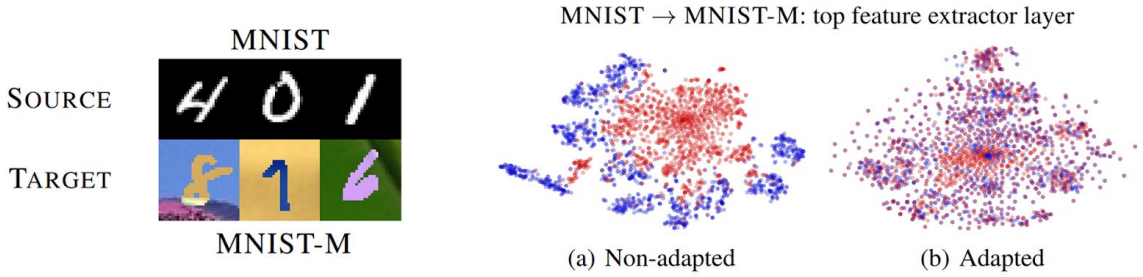

Figure 1. Left example source and target domains, right figure shows t-SNE visualizations of a CNN's activations (a) in case when no adaptation was performed and (b) in case when a domain adaptation procedure was incorporated into training. Blue points correspond to the source domain examples, while red ones correspond to the target domain. The domain adaptation makes the two distributions of features much closer [8].

Roadmap:

- **Literature Review**
  - Familiarize yourself with the current literature on Domain Adaptation [1]
  - Literature on Open Set Domain Adaptation problem [2-3]

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    - Literature on Disentangled Representative in Domain Adaptation [4-7]
- **Implementation:**
    - Implement a few baselines
    - Implement the proposed method
- **Experimental Results and Analysis:**
    - Comparison to SOTA
    - Extensive analysis and ablation study

Requirements:

- Solid background in Machine/Deep Learning
- Familiar with generative models, AEs, VAEs, ...etc.
- Sufficient knowledge of Python programming language and libraries (Scikit-learn, NumPy, ...)
- Experience with a mainstream deep learning framework such as PyTorch or Tensorflow.
- Machine/Deep learning hands-on experience

References:

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[3] Zhang, J., Ding, Z., Li, W. and Ogunbona, P., 2018. Importance weighted adversarial nets for partial domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 8156-8164). (PDF)

[4] Lee, H.Y., Tseng, H.Y., Mao, Q., Huang, J.B., Lu, Y.D., Singh, M. and Yang, M.H., 2020. Drit++: Diverse image-to-image translation via disentangled representations. *International Journal of Computer Vision*, pp.1-16. (PDF)

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[6] Liu, Y.C., Yeh, Y.Y., Fu, T.C., Wang, S.D., Chiu, W.C. and Frank Wang, Y.C., 2018. Detach and adapt: Learning cross-domain disentangled deep representation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 8867-8876). (PDF)

[7] Liu, A.H., Liu, Y.C., Yeh, Y.Y. and Wang, Y.C.F., 2018. A unified feature disentangler for multi-domain image translation and manipulation. In *Advances in neural information processing systems* (pp. 2590-2599). (PDF)

[8] Ganin, Y. and Lempitsky, V., 2015, June. Unsupervised Domain Adaptation by Backpropagation. In International Conference on Machine Learning (pp. 1180-1189). (PDF)

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