Note: DiRA: Discriminative, Restorative, and Adversarial Learning for Self-supervised Medical Image Analysis

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1 Introduction

This paper combines the discriminative model, restorative model and adversarial model together to foster collaborative learning for semantic representation. This paper also mentioned that medical image segmentation requires more subtle and fin-grained discriminative features compared to normal CV segmentation tasks. Thsi explains why restorative learning is preferred in medical imaging while discriminative learning is preferred in computer vision.
The main contribution is that this paper proposed DiRA that seamlessly unites discriminative, restorative and adversarial learning in a unified manner, setting a new SOTA for SSL in medical imaging.

2 Method

In the graph, we can see that this model consists of 3 main components. All the components are described below:

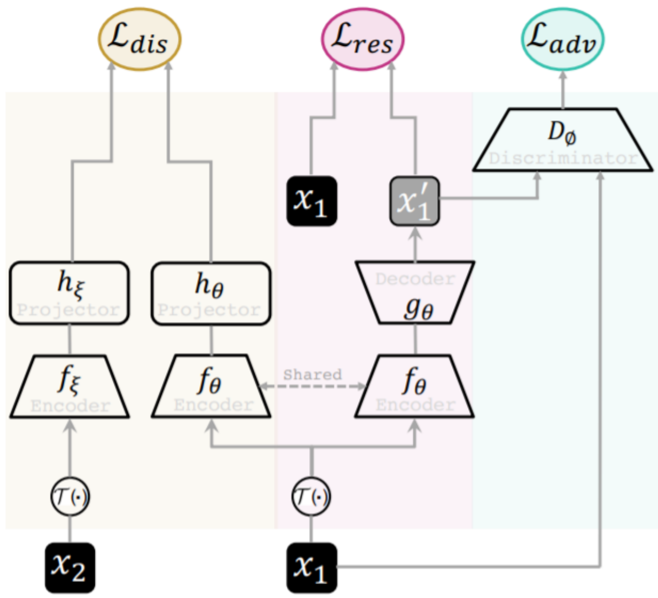

Figure 3. **Our proposed framework.** DiRA consists of three learning components: discriminative, restorative, and adversary. Given two input patches x_1 and x_2, we perturb them with $\mathcal{T}(.)$ and provide them as input to discrimination and restoration branches. The discrimination branch consists of encoders f_θ and f_ξ, and projectors h_θ and h_ξ, and maximizes the agreement between (high-level) embedding vectors of samples from the same (pseudo) class. The restoration branch consists of encoder f_θ and decoder g_θ, and maximizes the (pixel-level) agreement between original sample x_1 and restored x_1'. Adversarial discriminator D_ϕ contrasts the original samples with the restored ones, reinforcing the restoration to preserve more fine-grained details.

2.1 Discriminative learning

f_θ is a regular encoder, while f_ξ can be a momentum encoder or share weights with f_θ. The loss is : $\mathcal{L}_{dis} = l(z_1, z_2)$. where x_1 and x_2 are form the same image or same cluster.

2.2 Restorative learning

The goal is to minimize the distance of the original image and the restored image. The loss is :$\mathcal{L}_{res} = \mathbb{E}_x dist(x_1, x_1')$.

2.3 Adversarial learning

Adversarial learning aims to reinforce f_θ by measuring how realistic the restored images are.

The loss: $$\mathcal{L}_{adv} = \mathbb{E}_x \left[log\ D_\phi(x_1)\right] + \mathbb{E}_x \left[log(1 - D_\phi(x_1'))\right]$$

2.4 Joint training

The final loss :

$$\mathcal{L} = \lambda_{dis} * \mathcal{L}_{dis} + \lambda_{res} * \mathcal{L}_{res} + \lambda_{adv} * \mathcal{L}_{adv}$$

3 Summary

DiRA is the first SSL framework that unites discriminative, restorative, and adversarial learning in a unified manner. This method achieves remarkable performance improvement, set the new SOTA.

References