## **Deep Learning**

## **Assignment 3 - VAE + Adversarial Learning**

**Deadline:** 11:59 PM, April 12th, 2019 Points: 200

In this assignment, the task is to train a VAE along with a discriminator on MNIST images.

Only Pytorch can be used as a DL library. This is going to be a fairly <u>long</u> assignment. Please start early!

- 1. Download the MNIST dataset.
- 2. Download the Multi-PIE face dataset
- 3. Train a VAE for each of the two datasets.
- 4. Train the architecture in <u>Disentangling factors of variation in deep representations using adversarial training</u>, NIPS 2016. You are permitted some modifications, which will be discussed in class. You are expected to **code this paper from scratch**. You cannot use code available on the web or elsewhere.
  - a. For MNIST, train the model with class labels as the specified factors of variation (Mandatory)
  - b. For faces, train the model with identity labels as the specified factors of variation (Optional: Extra Credit 50 points)

## Following details are to be mentioned in the report:

- 1. Show a grid of generated images from VAEs in MNIST and the face dataset.
- 2. Show t-SNE plots of specified factors space, color coded by the labels; Similarly show t-SNE plots of unspecified factors latent space, color coded by the labels. Something similar to Fig. 5 in [2]
- 3. Show transfer of specified and unspecified factors on both MNIST and the faces dataset. Similar to Fig. 2(a) in [1] and Fig. 6 in [2].
- 4. Using loss plots and any other analyses, show that the training of the discriminator has stabilized.
- 5. Train two classifiers (both two layer MLPs as described in Sec. 4.1 in [2]) for predicting class labels with input as the specified factor latent vectors and the unspecified factors latent vectors. Report the accuracy on each.

Save your best model so that it can be used during evaluation.

## References

- [1] Mathieu et al., <u>Disentangling factors of variation in deep representations using adversarial training</u>, NIPS 2016
- [2] Jha et al., <u>Disentangling Factors of Variation with Cycle-Consistent Variational</u>
  <u>Auto-Encoders</u>, ECCV 2018