Summary

During the past week, in order to better evaluate the proposed method, instead of only comparing with random initializer, I also compared my method with three other initializers [1, 2, 3] that are well-known in Keras library. I developed more experiments to make a stronger evaluation. Also in order to compare the effect of different factors, I modified the number of samples and number of epochs same as before.

Data

In these experiments, instead of only using four classes of MNIST I used all of the 10 classes. I ran two experiments using the whole dataset, and two experiment only using a small portion of it (250 sample for each class, 200 for training and 50 for testing). For each data set two experiments with different number of epochs were implemented.

Results and Conclusions

Fig. 1 demonstrates the error bar of loss drop resulted by running the experiment for 10 iterations and Fig. 2 indicates the reconstructed images using different initializers in 1 iteration. The following results confirm that NNMF initializer has superiority both in terms of faster learning and lower variance (specially when the number of samples are small (Fig. 1 (c,d)).

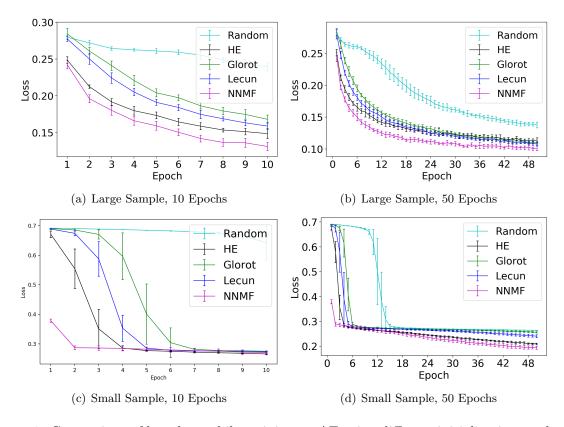


Figure 1: Comparison of loss drop while training an AE using different initialization methods.

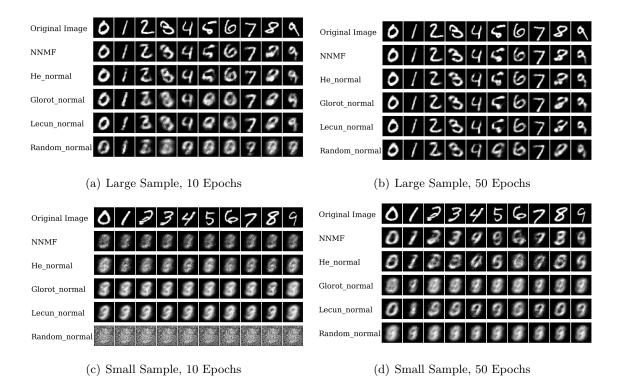


Figure 2: Comparison of original image, reconstructed image by an AE using different initialization methods.

What to do next week?

Although it seems that this research is very applicable and the result are promising, there are still some major problems that I have to address during the following week.

- The topic is not hot enough. \rightarrow I should look for a hot area that this research is applicable for.
- ullet The methods that I am using for comparison are out-dated. \to I should look for more recent methods for initialization.
- The evaluation is not strong enough. \rightarrow I should apply the method on another dataset and test it.

References

- [1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings* of the IEEE international conference on computer vision, pages 1026–1034, 2015.
- [2] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference* on artificial intelligence and statistics, pages 249–256, 2010.
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