Representation learning using autoencoders:

- The objective is to experiment with representation learning. We simply use autoencoders as the models so that the implementation will be straightforward. You can make use of existing codes on the web.
- Since the objective is representation learning, reconstruction is considered the pretext task, and we will use the encoder, which converts any input to the embedding, for other downstream tasks.
- For datasets, start with common basic datasets like MNIST handwritten digits, handwritten characters, CIFAR-10, or similar ones. You can add additional image datasets if you want.
- You can use several types of modifying the input images for the pretext task. Denoising is considered a type of self-prediction, but you can add things like random masking as well. You can later compare the performance (for downstream tasks) with encoders trained differently.
- For downstream tasks, we can do both classification (using simple classical classifiers like kNN, naïve Bayes, SVM, or single-hidden-layer MLP, etc.) and clustering. Take the embedding of the images as inputs to the classification/clustering algorithms.
- Additional comparison of results: You can try to see the results are affected by the embedding length. You can also compare the results with those obtained when the images are just projected by PCA to vectors of the same dimensionality as your embedding.
- Cross-dataset experiments: For example, you do the pretraining with MNIST handwritten digits and then try to classify handwritten characters (A-Z only). What is the performance?
- All the experiments mentioned above are optional, and you can decide what you want to and are able to do. You can also think of additional experiments.
- Report length: within 5-10 pages single-spaced, not counting code listings. PDF file only. Submit through E3.
- Due date: **6/21** (no late submission accepted)