Supplementary material for
On Deep Multi-View Representation Learning

Weiran Wang WEIRANWANG@TTIC.EDU
Toyota Technological Institute at Chicago

Raman Arora ARORA@CS.JHU.EDU
Johns Hopkins University

Karen Livescu KLIVESCU@TTIC.EDU
Toyota Technological Institute at Chicago

Jeff Bilmes BILMES@EE.WASHINGTON.EDU
University of Washington, Seattle

In this supplementary material, we give visualizations of projected view 1 test images of the noisy MNIST dataset by all feature learning algorithms in Figure 1 (including an embedding of input features with images) and Figure 2.

References

Vladymyrov, Max and Carreira-Perpiñán, Miguel Á. Partial-Hessian strategies for fast learning of nonlinear embeddings. In *Proc. of the 29th Int. Conf. Machine Learning (ICML 2012)*, pp. 345–352, 2012.

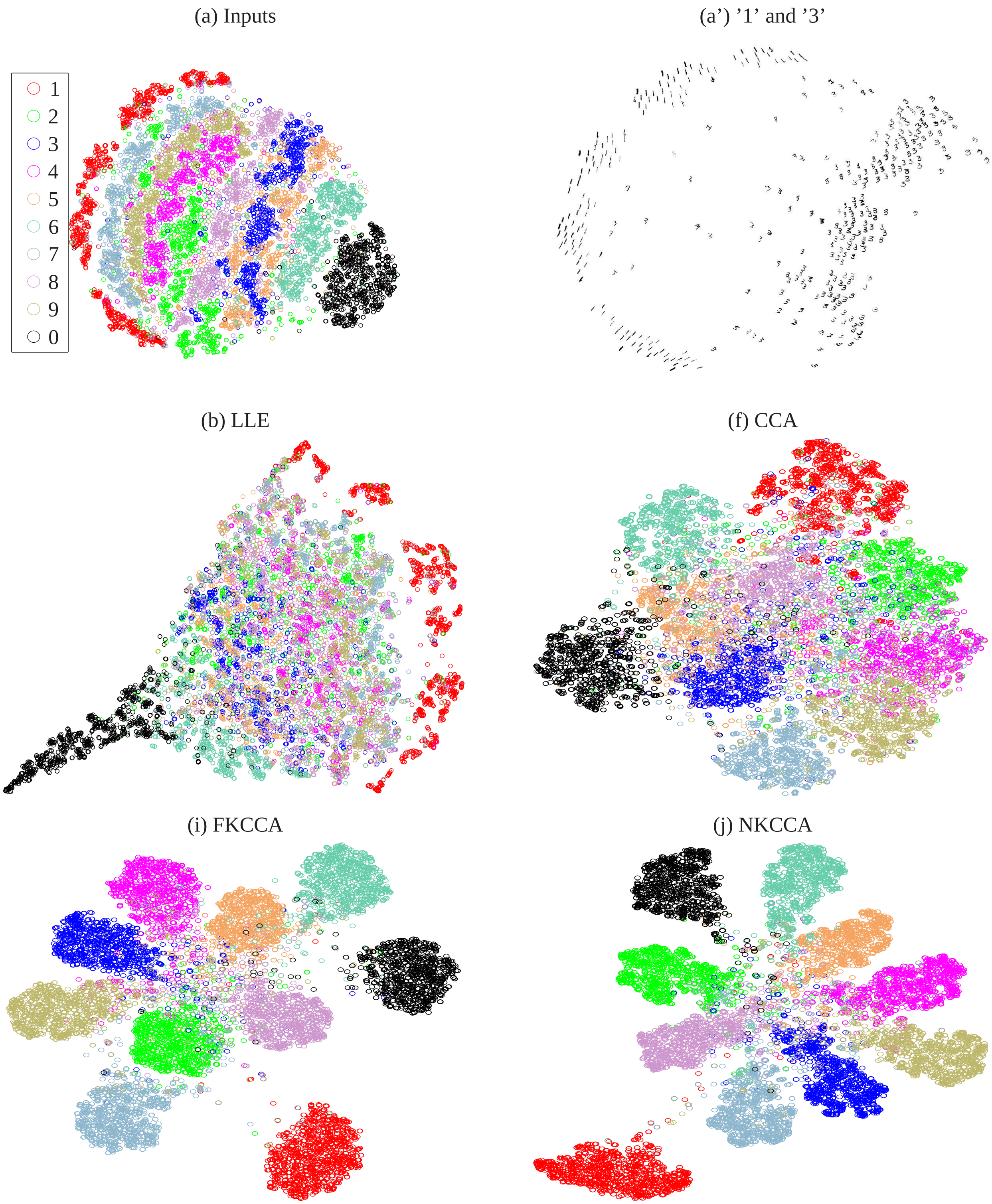

Figure 1. t-SNE embedding of the projected test set of noisy MNIST digits by different algorithms. Each sample is denoted by a marker located at its coordinates of embedding and color coded by its identity, except in (a') where the actual input image is shown for samples of classes '1' and '3'. Neither the feature learning algorithms nor t-SNE is aware of the class information. We have run the t-SNE implementation of Vladymyrov & Carreira-Perpiñán (2012) on the $10\,000$ projected test images for 300 iterations with a perplexity of 20.

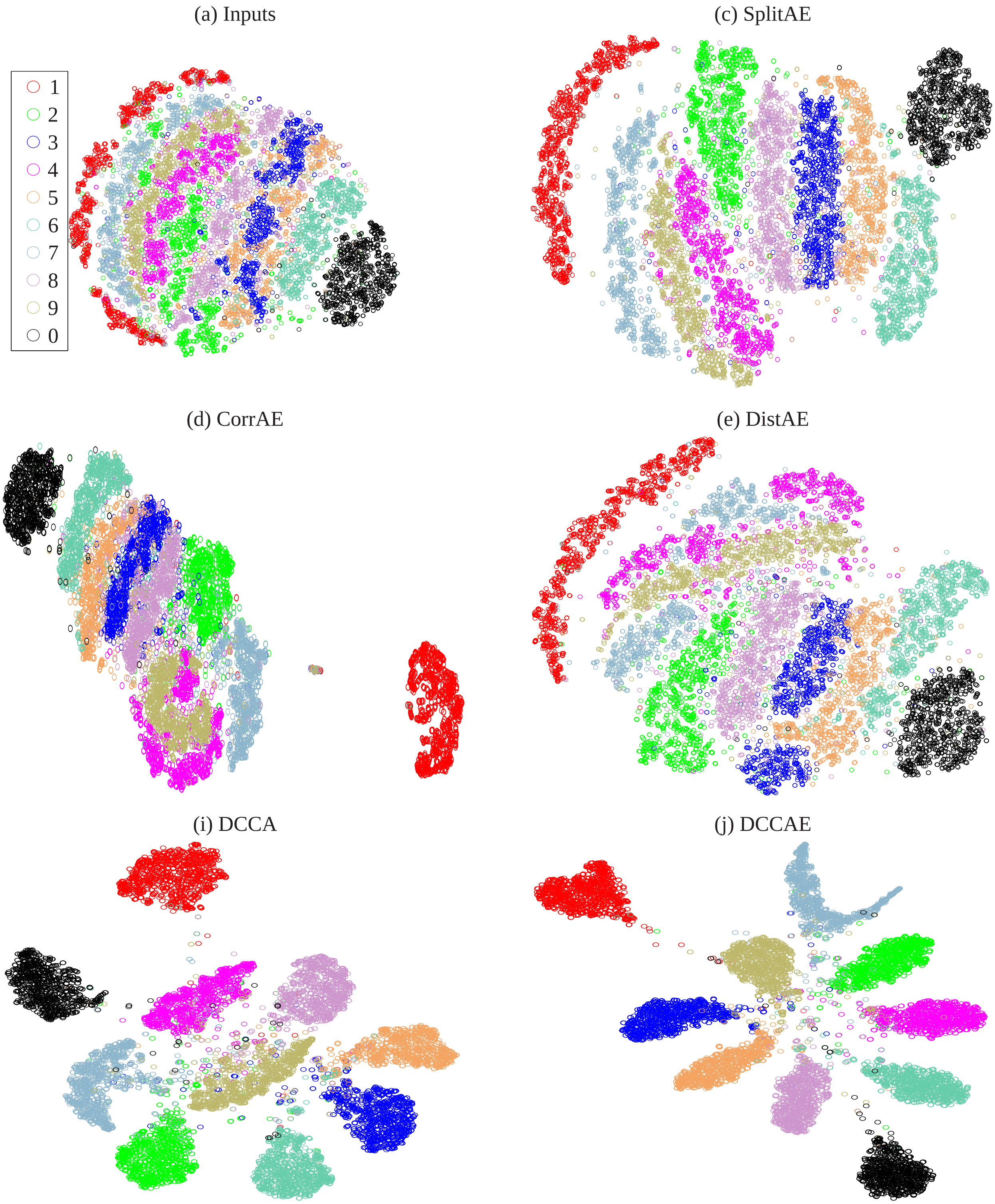

Figure 2. t-SNE embedding of the projected test set of noisy MNIST digits by different algorithms. Each sample is denoted by a marker located at its coordinates of embedding and color coded by its identity. Neither the feature learning algorithms nor t-SNE is aware of the class information. We have run the t-SNE implementation of Vladymyrov & Carreira-Perpiñán (2012) on the $10\,000$ projected test images for 300 iterations with a perplexity of 20.