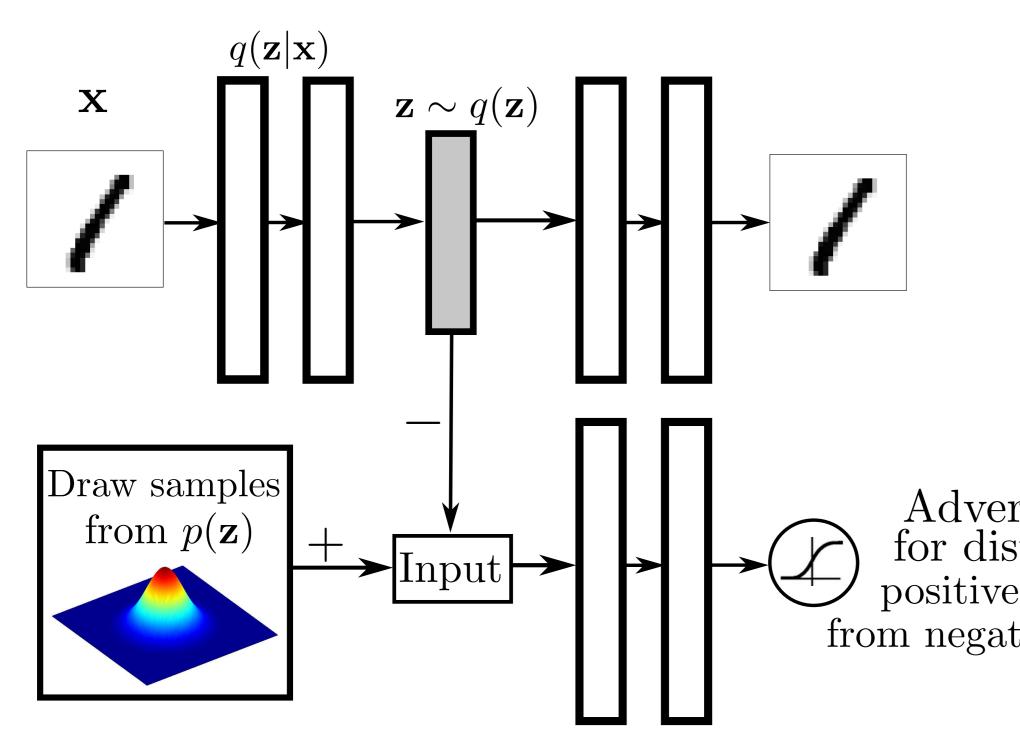


ADVERSARIAL AUTOENCODERS (AAE)

We propose a new method for regularizing autoencoders by imposing an arbitrary prior on the latent representation of the autoencoder with GAN framework.

Training has two stages:

- The autoencoder updates the encoder and the decoder to minimize the reconstruction error.
- The adversarial network first updates its discriminator to tell the apart the true samples from the generated samples then updates its generator to confuse the discriminator.



RELATIONSHIP TO VAE

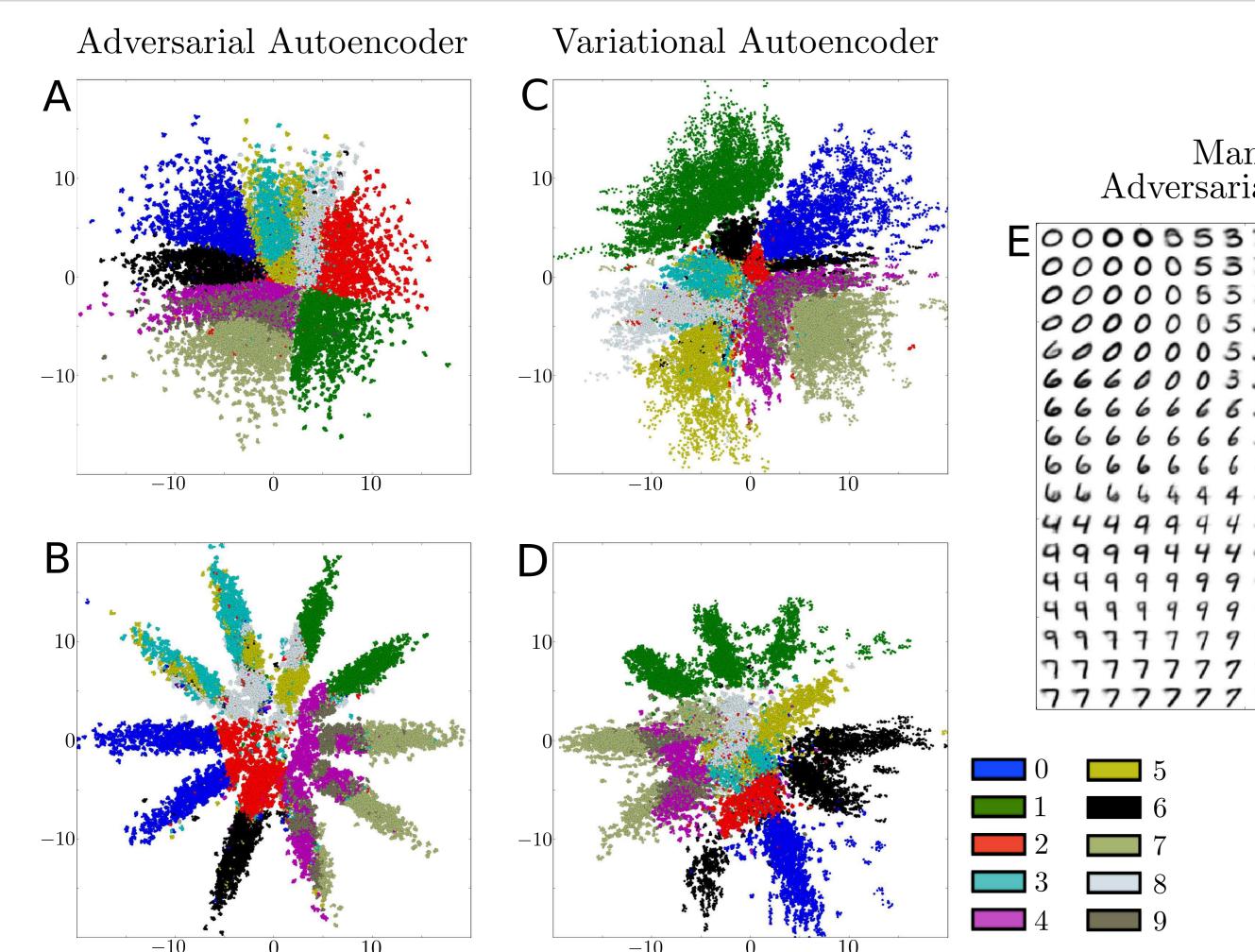


Figure 1: (a) 2-D Gaussian code of AAE (b) mixture of 10 2-D Gaussian code of AAE (c) 2-D Gaussian code of VAE (d) mixture of 10 2-D Gaussian code of VAE (e) AAE manifold.

Adversarial Autoencoders Alireza Makhzani, Jonathon Shlens, Navdeep Jaitly, Ian Goodfellow

Google Brain

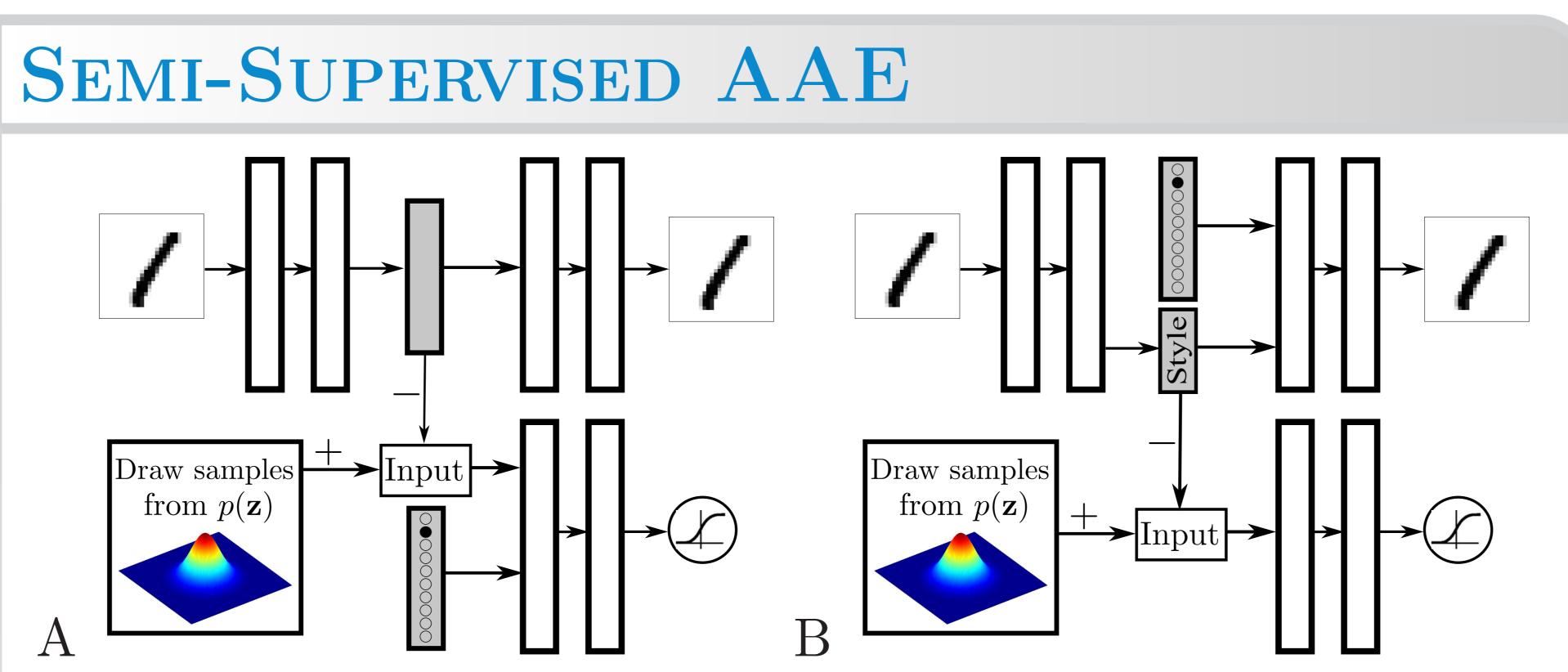


Figure 2: Two methods for semi-supervised learning with AAE (a) Regularizing the hidden code by providing a one-hot vector to the discriminative network. (b) Disentangling the label information from the hidden code by providing the one-hot vector to the generative model.

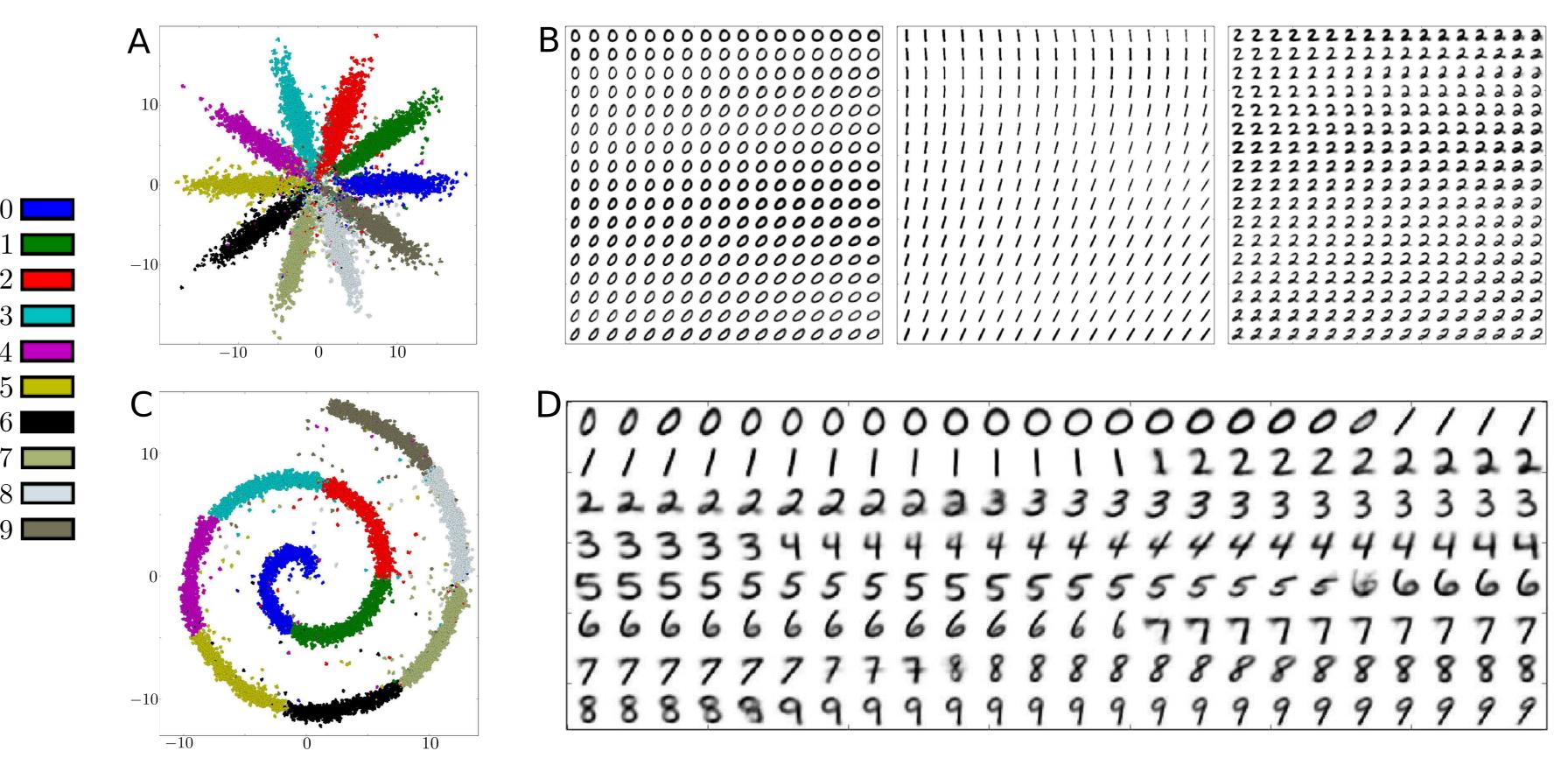
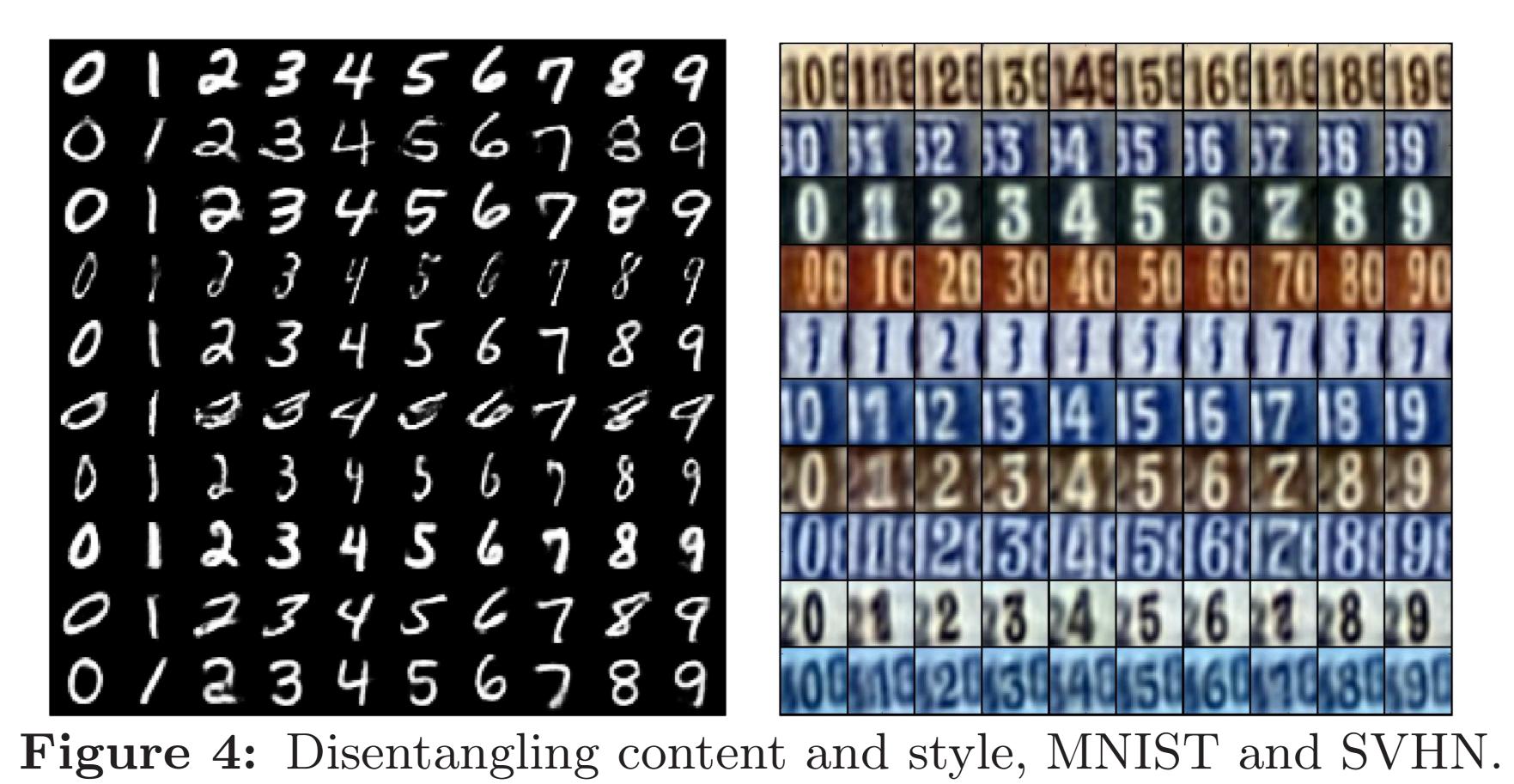


Figure 3: Leveraging label information to better regularize the hidden code. (a,b) Training the coding space to match a mixture of 10 2-D Gaussians. (c,d) Same but for a swiss roll distribution.





LIKELIHOOD EVALUATION



DBN Stacked CAE Deep GSN GAN GMMN + AEAAE

Table 1: Log-likelihood of test data on MNIST and Toronto Face dataset. Higher values are better. On both datasets we report the Parzen window estimate of the log-likelihood obtained by drawing 10K or 10M samples from the trained model.

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2016

Figure 5: Samples generated from an adversarial autoencoder trained on MNIST and TFD. The last column shows the closest training images in pixel-wise Euclidean distance to those in the second-to-last column.

	MNIST	MNIST	TFD	TFD
	(10K)	(10M)	(10K)	(10M)
	138 ± 2	_	1909 ± 66	_
	121 ± 1.6		2110 ± 50	_
	214 ± 1.1		1890 ± 29	_
	225 ± 2	386	2057 ± 26	-
Ē	282 ± 2		2204 ± 20	_
	340 ± 2	427	$\boxed{2252\pm16}$	2522