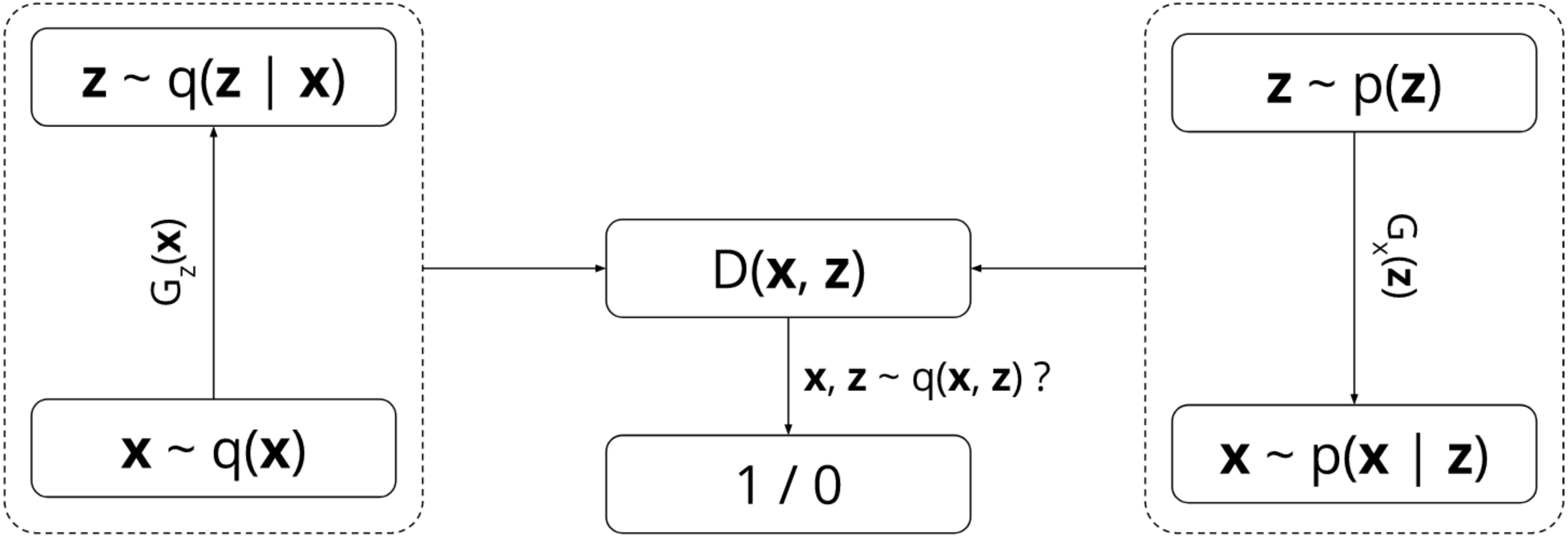
ENM 540: Data-driven modeling and probabilistic scientific computing

Convergence of variational and adversarial learning

Paris Perdikaris
April 12, 2018

Adversarially learned inference

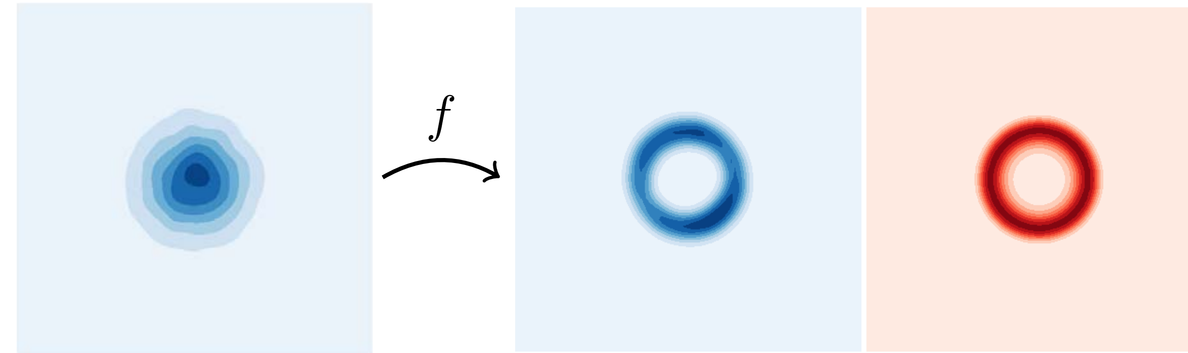


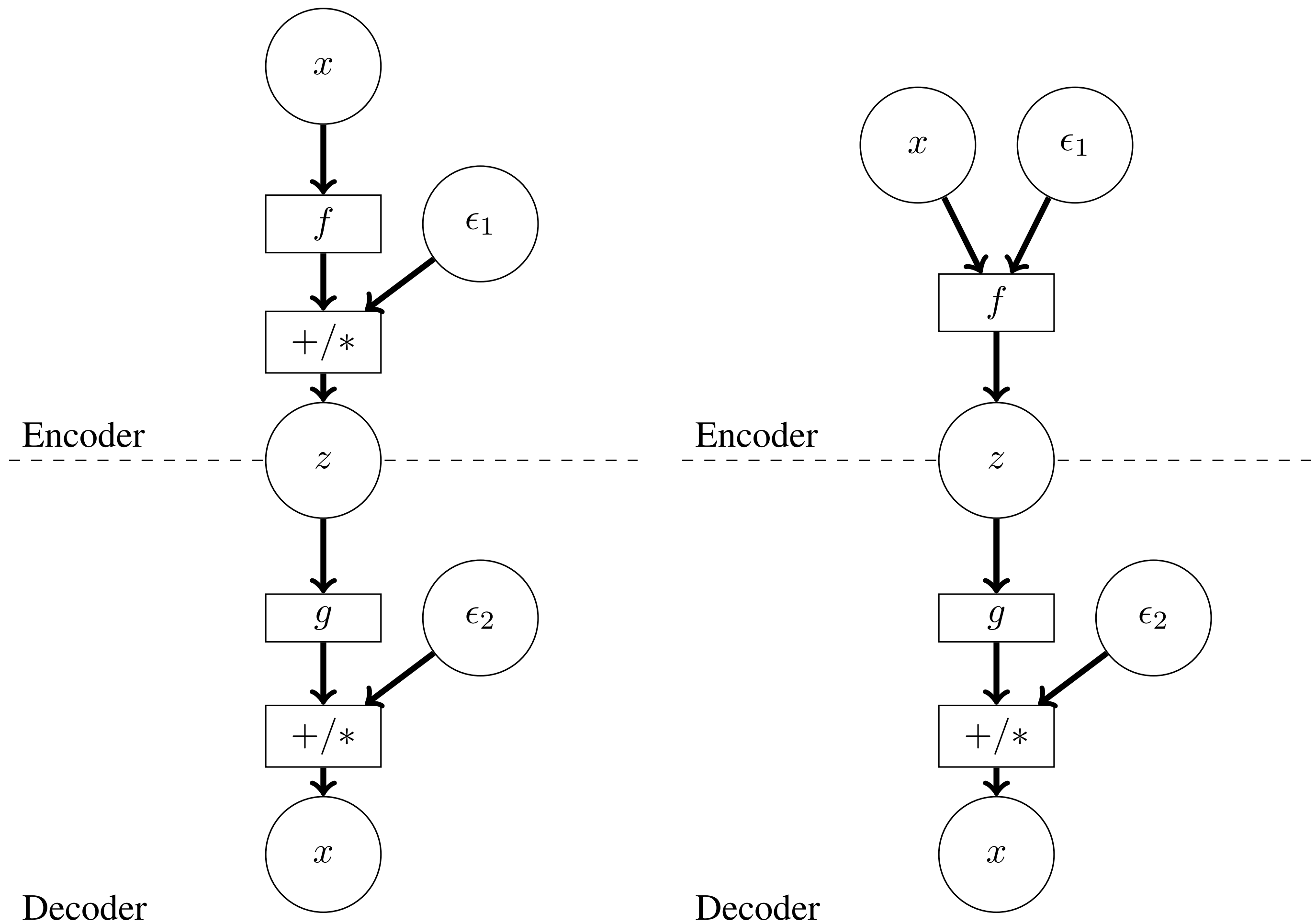
$$\min_G \max_D V(D, G) = \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}, G_z(\mathbf{x})))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G_x(\mathbf{z}), \mathbf{z}))]$$

Dumoulin, V., Belghazi, I., Poole, B., Mastropietro, O., Lamb, A., Arjovsky, M., & Courville, A. (2016). Adversarially learned inference. arXiv preprint arXiv:1606.00704.

Adversarial Variational Bayes

Instead of using approximating distributions of a given pre-defined form (e.g. Gaussian) we can implicitly parametrize them using deep neural networks.





(a) Standard VAE

(b) Our model

Algorithm 1 Adversarial Variational Bayes (AVB)

$i \leftarrow 0$

while not converged **do**

Sample $\{x^{(1)}, \ldots, x^{(m)}\}$ from data distrib. $p_{\mathcal{D}}(x)$

Sample $\{z^{(1)}, \ldots, z^{(m)}\}$ from prior $p(z)$

Sample $\{\epsilon^{(1)}, \ldots, \epsilon^{(m)}\}$ from $\mathcal{N}(0,1)$

Compute θ-gradient (eq. 3.7):

$$g_\theta \leftarrow \frac{1}{m}\sum_{k=1}^{m} \nabla_\theta \log p_\theta\left(x^{(k)} \mid z_\phi\left(x^{(k)}, \epsilon^{(k)}\right)\right)$$

Compute ϕ-gradient (eq. 3.7):

$$g_\phi \leftarrow \frac{1}{m}\sum_{k=1}^{m} \nabla_\phi\big[-T_\psi\left(x^{(k)}, z_\phi(x^{(k)}, \epsilon^{(k)})\right) + \log p_\theta\left(x^{(k)} \mid z_\phi(x^{(k)}, \epsilon^{(k)})\right)\big]$$

Compute ψ-gradient (eq. 3.3) :

$$g_\psi \leftarrow \frac{1}{m}\sum_{k=1}^{m} \nabla_\psi\Big[\log\left(\sigma(T_\psi(x^{(k)}, z_\phi(x^{(k)}, \epsilon^{(k)})))\right) + \log\left(1 - \sigma(T_\psi(x^{(k)}, z^{(k)}))\right)\Big]$$

Perform SGD-updates for θ, ϕ and ψ:

$\theta \leftarrow \theta + h_i\, g_\theta, \quad \phi \leftarrow \phi + h_i\, g_\phi, \quad \psi \leftarrow \psi + h_i\, g_\psi$

$i \leftarrow i + 1$

end while

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Mescheder, L., Nowozin, S., & Geiger, A. (2017). Adversarial variational Bayes: Unifying variational autoencoders and generative adversarial networks. arXiv preprint arXiv: 1701.04722.

Pu, Y., Chen, L., Dai, S., Wang, W., Li, C., & Carin, L. (2017). Symmetric variational autoencoder and connections to adversarial learning. arXiv preprint arXiv:1709.01846.

Makhzani, A., Shlens, J., Jaitly, N., Goodfellow, I., & Frey, B. (2015). Adversarial autoencoders. arXiv preprint arXiv:1511.05644.