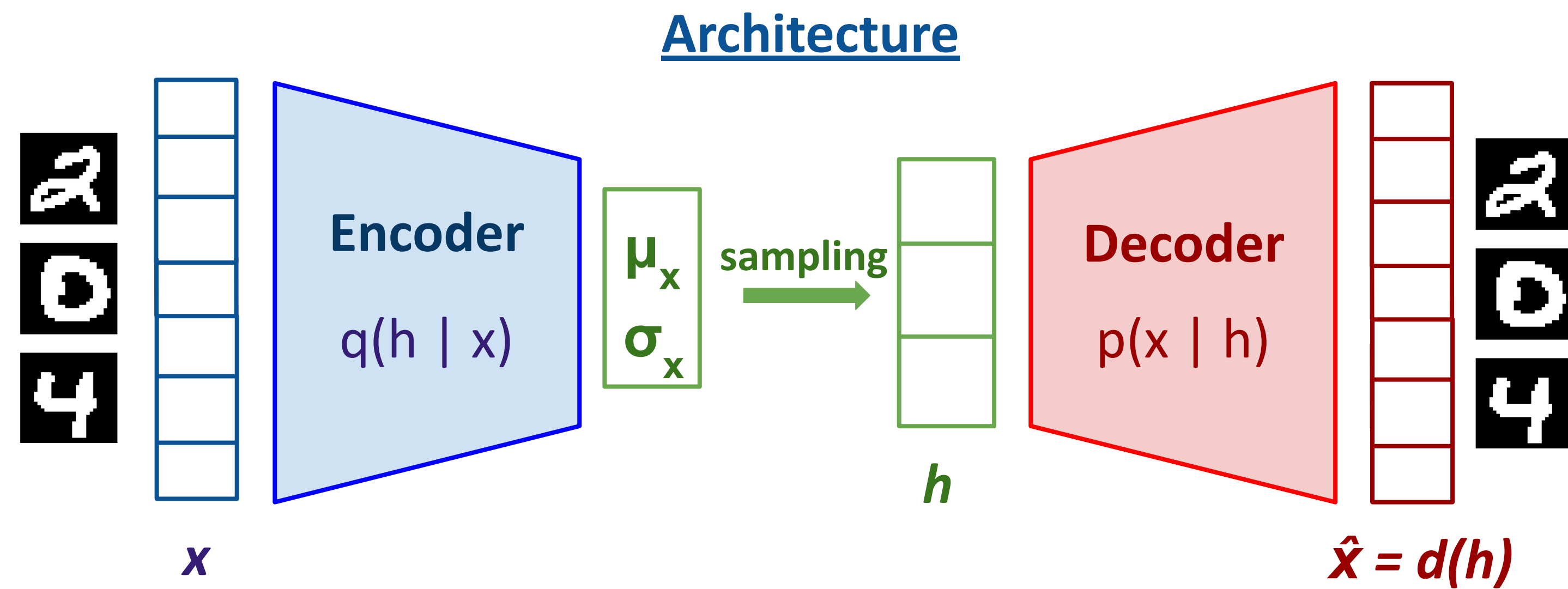


Importance Weighted Autoencoder (IWAE)

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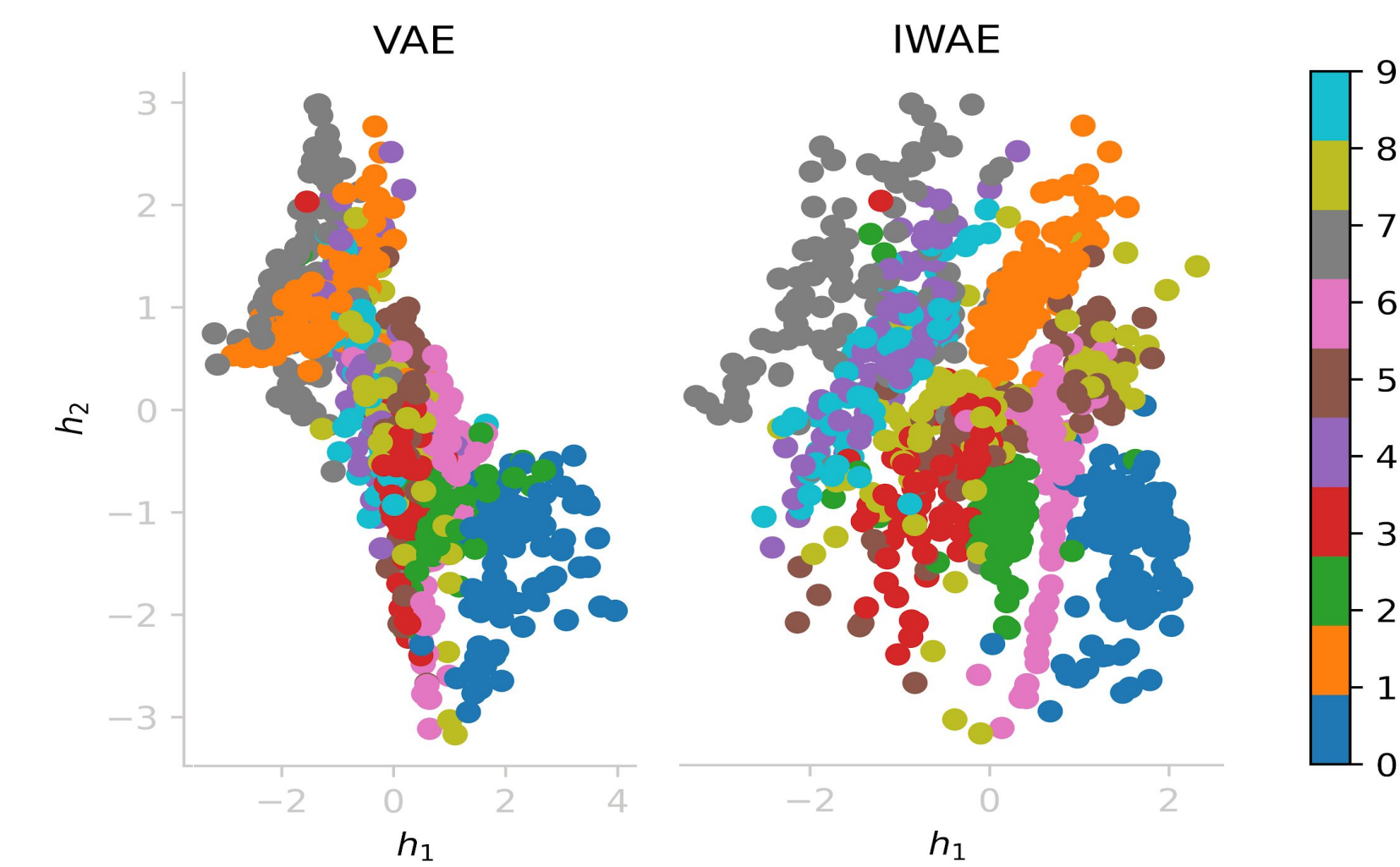
MNIST results

k	VAE		IWAE	
	Log-likelihood	Reconstruction Loss	Log-likelihood	Reconstruction Loss
1	-89.87	71.87	-89.87	71.87
5	-89.85	72.09	-87.61	71.63
50	-90.81	74.15	-87.13	78.36

Log-likelihood and reconstruction loss for models with one stochastic layer on the fixed binarization MNIST dataset [1]

Classical VAE	IWAE
$\mathcal{L}_{VAE}(x) = \mathbb{E}_{q(h x)} \left[\log \left(\frac{p(x, h)}{q(h x)} \right) \right] \cong \sum_{h_1, \dots, h_k \sim q(h x)} \frac{1}{k} \log \left(\frac{p(x, h_i)}{q(h_i x)} \right)$	$\mathcal{L}_{IWAE}^k(x) = \mathbb{E}_{h_1, \dots, h_k \sim q(h x)} \left[\log \left(\frac{1}{k} \sum_{i=1}^k \frac{p(x, h_i)}{q(h_i x)} \right) \right] \cong \sum_{h_1, \dots, h_k \sim q(h x)} \log \left(\frac{1}{k} \sum_{i=1}^k \frac{p(x, h_i)}{q(h_i x)} \right)$

IWAE learns a more spread-out latent representation

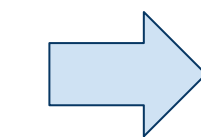


Also addressed in our report

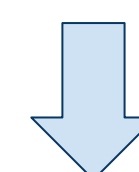
- Generalisation to N stochastic layers
- Other datasets (OMNIGLOT)
- Investigation of the true latent space representation dimension
- Similar loss functions: $\mathcal{L}_p^k(x) = \mathbb{E}_{h_1, \dots, h_k \sim q(h|x)} \left[\log \left(\left[\frac{1}{k} \sum_i \left(\frac{p(x, h_i)}{q(h_i|x)} \right)^p \right]^{\frac{1}{p}} \right) \right]$

Analysis

$$\log(p(x)) \geq \mathcal{L}_{IWAE}^k(x) \geq \mathcal{L}_{VAE}(x) = \log(p(x)) - D_{KL}(q(h|x) || p(h|x))$$



Weaker constraints on the posterior approximation

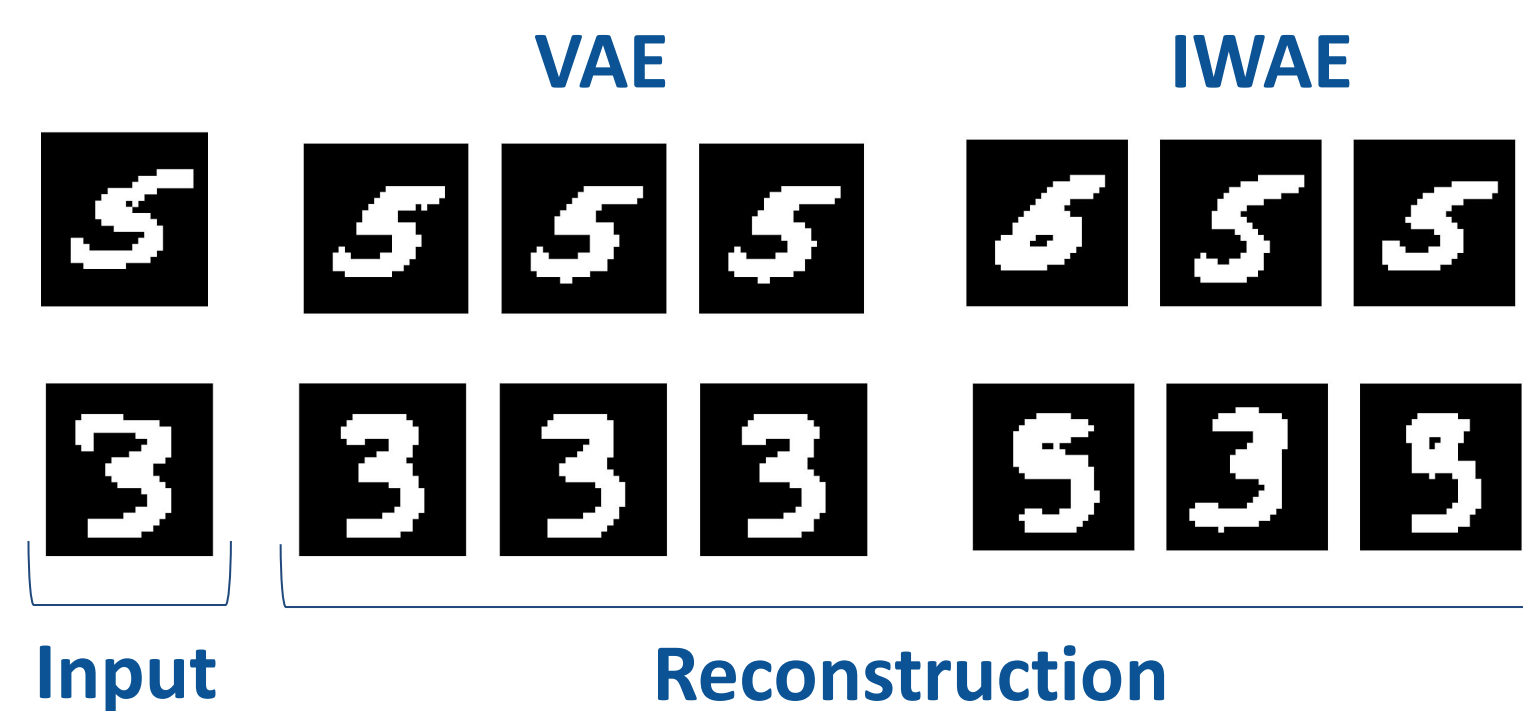


Pros

- ✓ Tighter lower-bound on the log-likelihood
- ✓ Richer latent representations

Cons

- ✗ Loss in encoding-decoding power



References

1. <https://www.tensorflow.org/datasets/catalog/mnist>
2. Kingma, D. P., and Welling M., "Auto-encoding variational bayes." arXiv preprint arXiv:1312.6114 (2013).
3. Yuri B., Roger G. and Ruslan S., "Importance Weighted Autoencoders" arXiv:1509.00519 (2015)