Disentangling Disentanglement in Variational Autoencoders

GenU 2019 (Originally Presented at ICML 2019)

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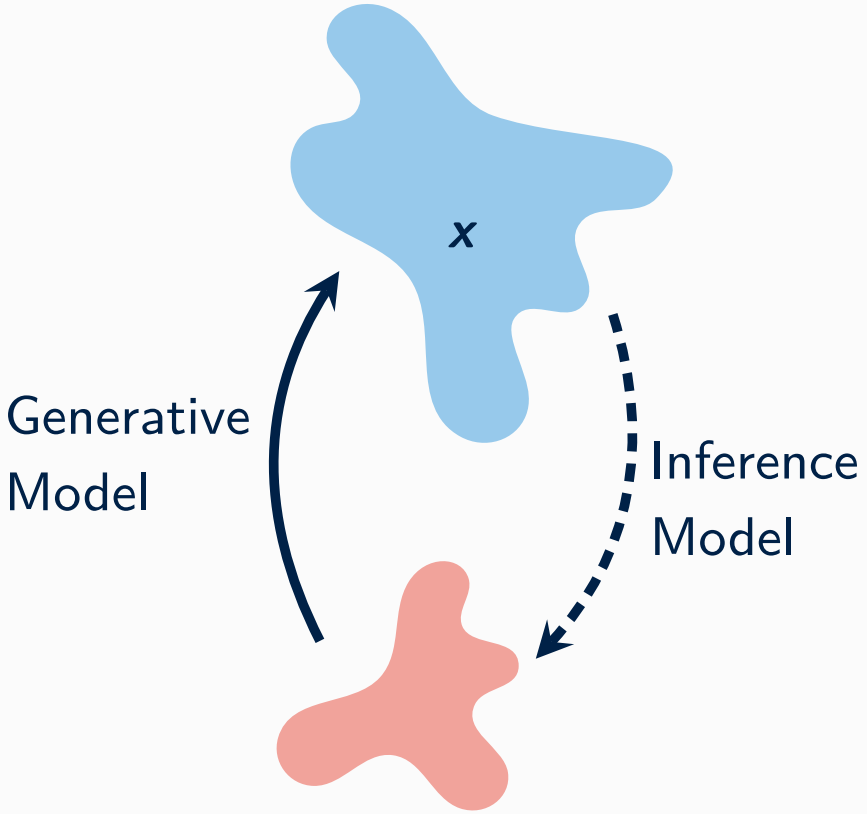
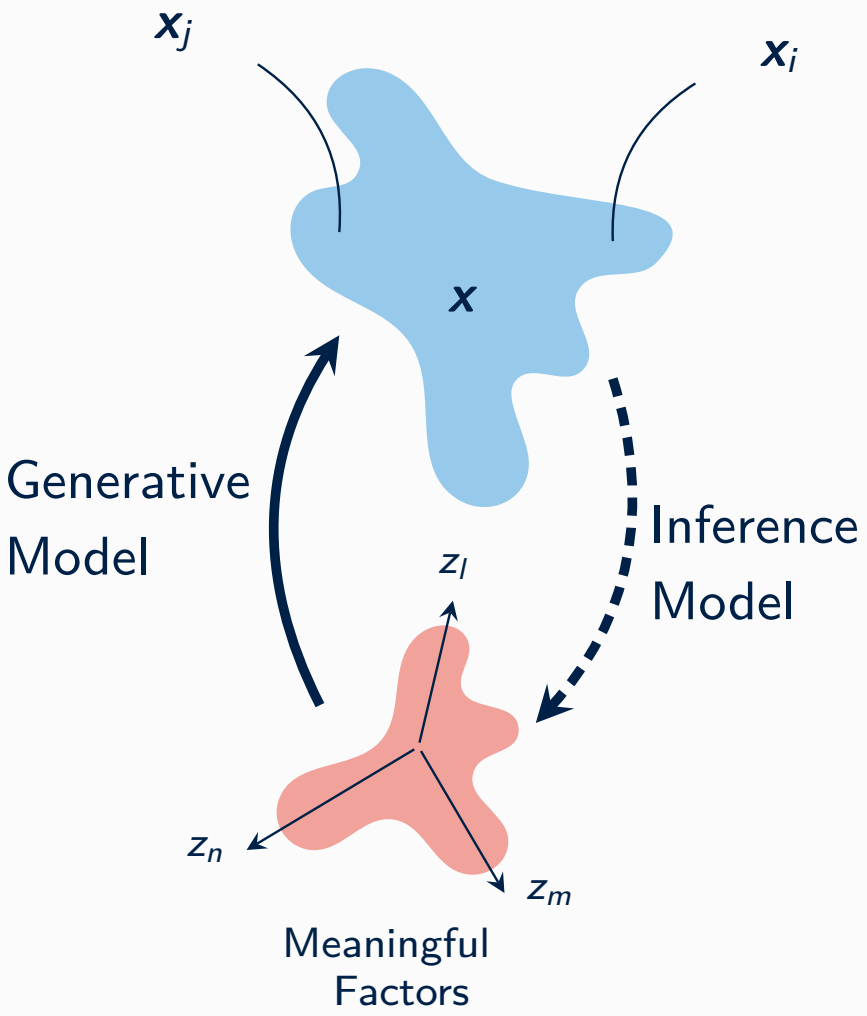
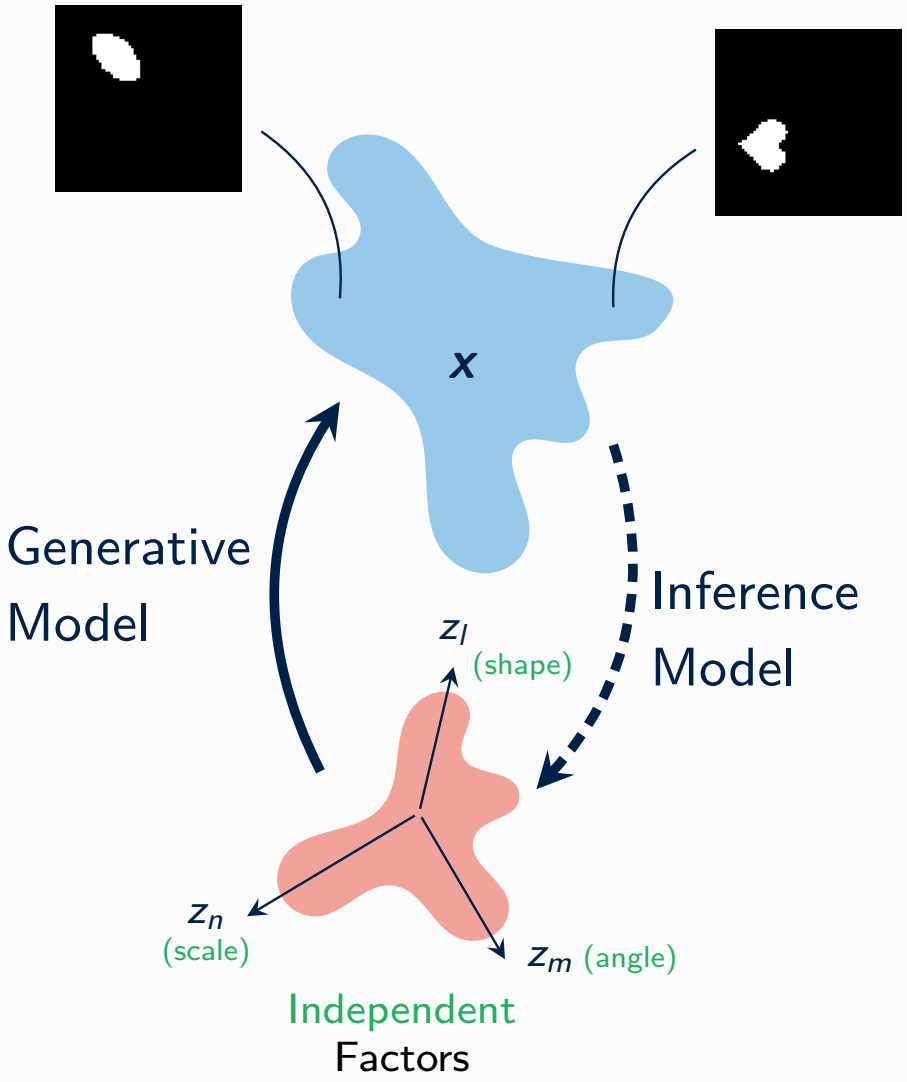
Variational Autoencoders



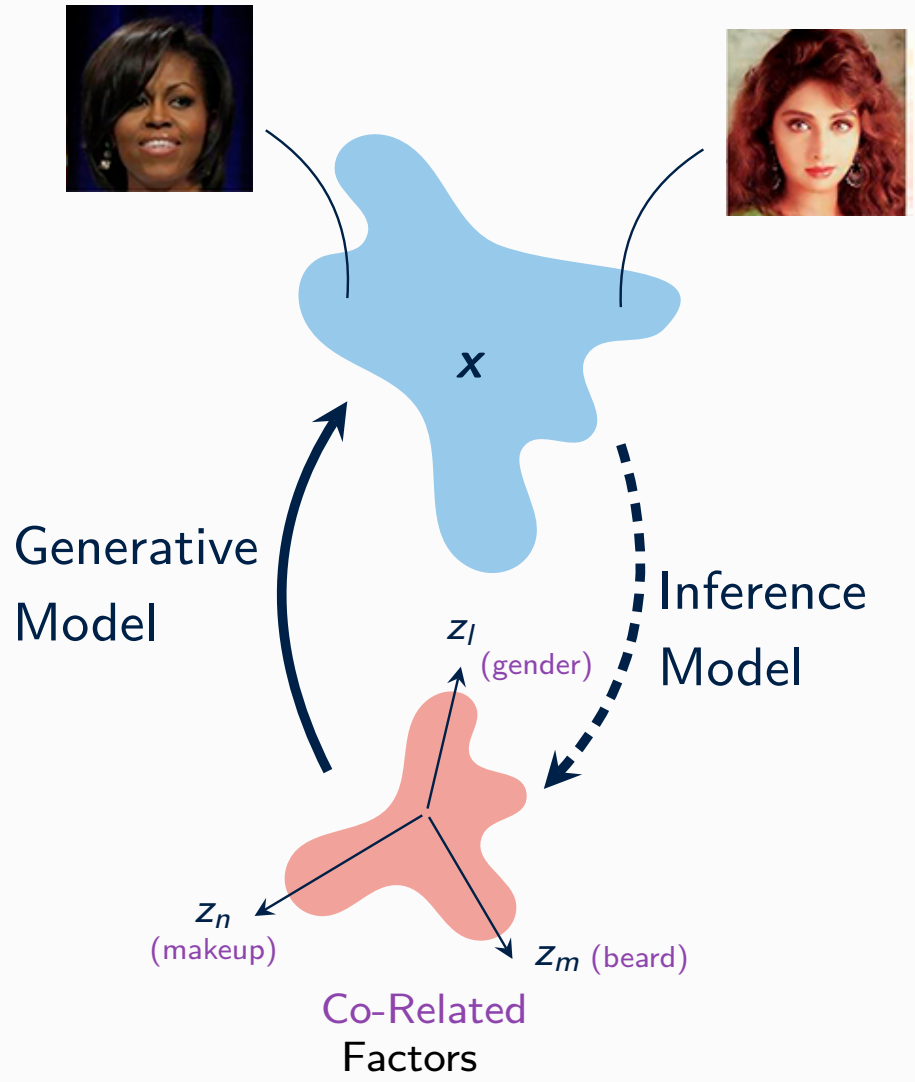
Interpretable Representations



Disentanglement = Independence



Decomposition $\in$ {Independence, Clustering, Sparsity, ...}



Talk Outline

- Background on VAEs and disentanglement

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- Points of discussion

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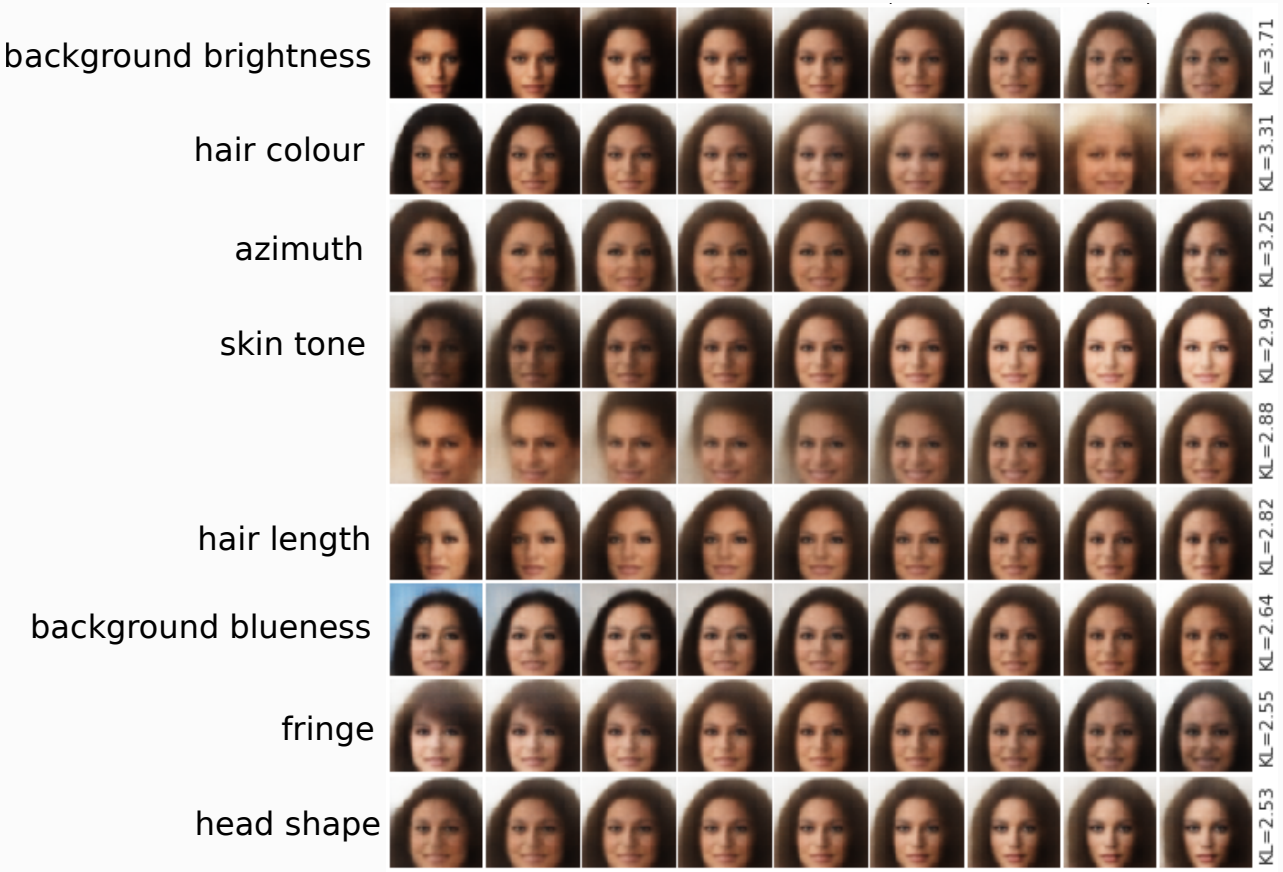
- VAE views this as a deep stochastic autoencoder, where $q_\phi(\boldsymbol{z}|\boldsymbol{x})$ is the encoder and $p_\theta(\boldsymbol{x}|\boldsymbol{z})$ the decoder

Disentanglement



[1] Hyunjik Kim and Andriy Mnih. "Disentangling by Factorising". In: *International Conference on Machine Learning*. 2018.

Disentanglement

- Care about the pushforward distribution of the data in latent space:

$$q_\phi(\boldsymbol{z}) = \mathbb{E}_{p_\mathcal{D}(\boldsymbol{x})}\left[q_\phi(\boldsymbol{z}|\boldsymbol{x})\right] \tag{2}$$

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- Some papers require z_d to correspond to "true generative factors"

Decomposition: A Generalization of Disentanglement

More general framework for imposing *meaningful* structure on learned representations

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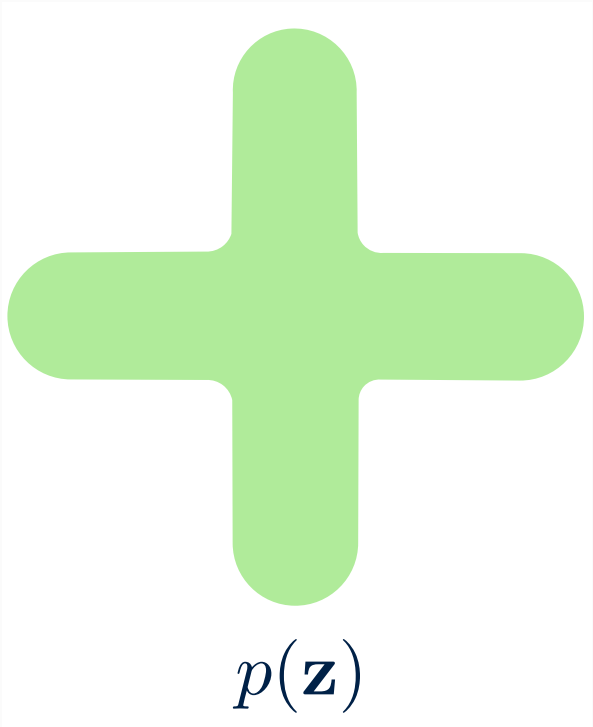
Characterise decomposition as the fulfilment of two factors:

(a) matching between the marginal posterior $q_\phi(\boldsymbol{z})$ and structured prior $p(\boldsymbol{z})$ to constrain with the required decomposition.

(b) appropriate level of overlap between encodings in the latent space,

Decomposition: An Analysis

Desired Structure



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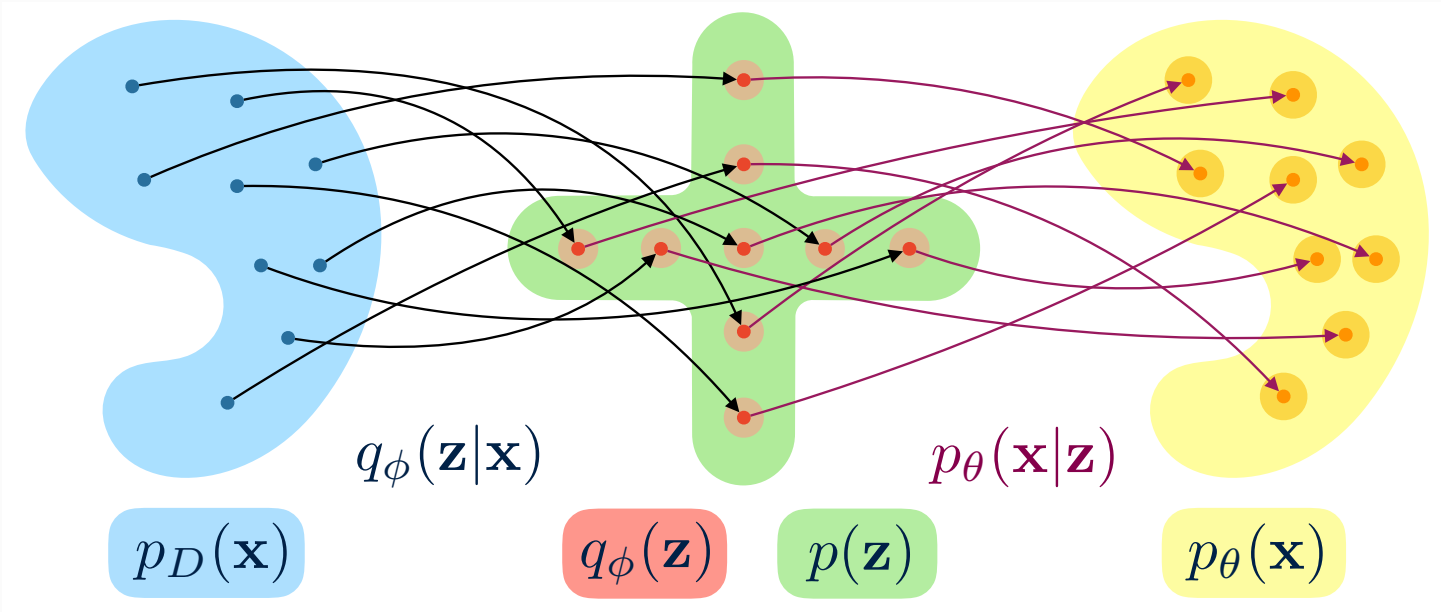

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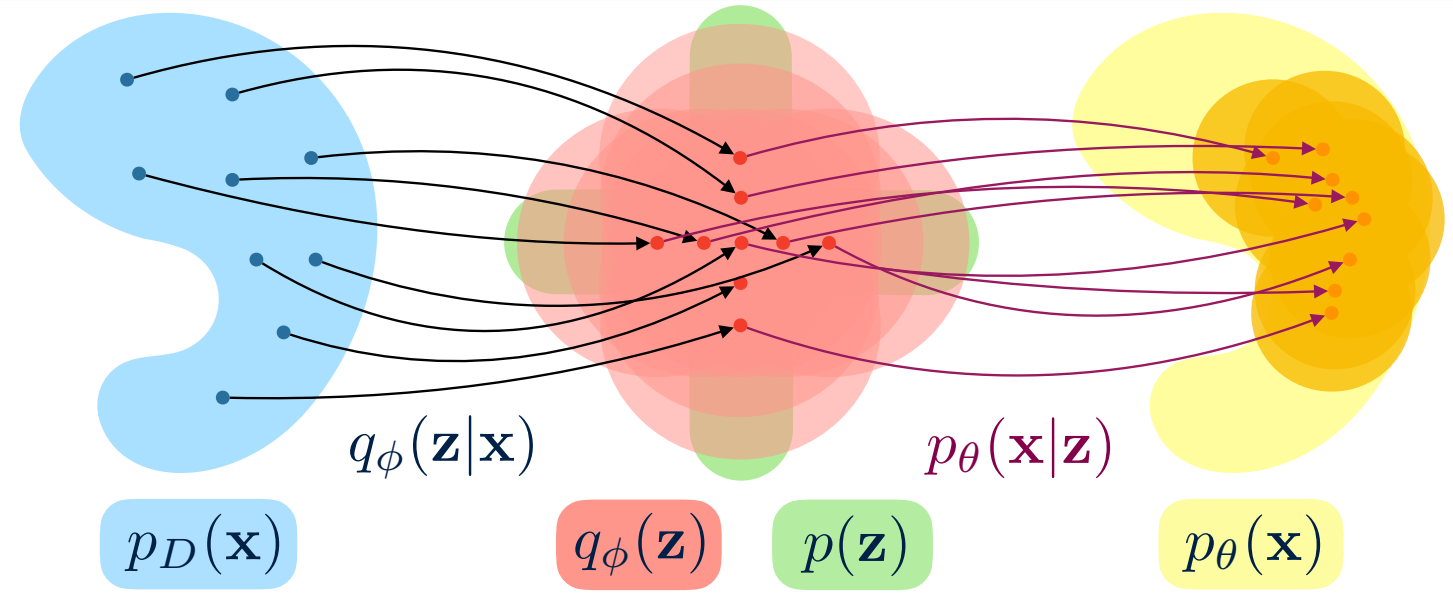
Too Much Overlap



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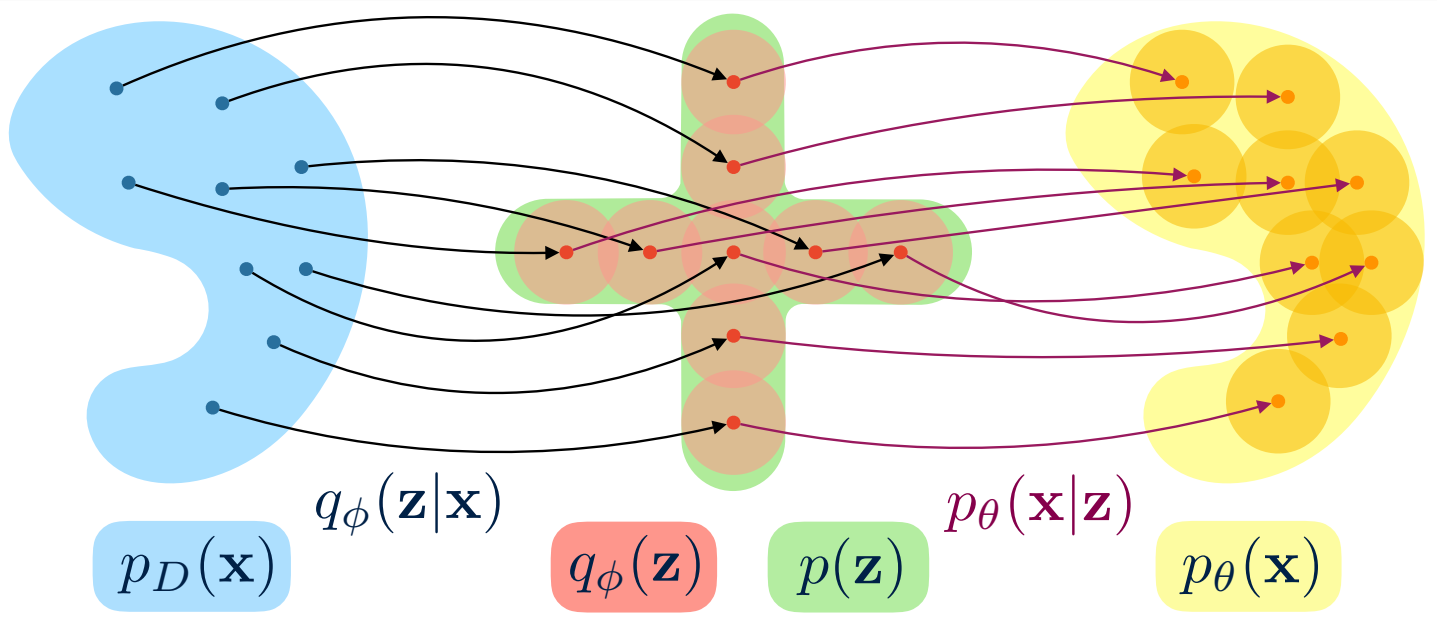
Appropriate Overlap



Deconstructing the β-VAE

The β-VAE[2] adjusts the standard ELBO by scaling the KL term:

$$\mathcal{L}_\beta(\boldsymbol{x}) = \mathbb{E}_{q_\phi(\boldsymbol{z}|\boldsymbol{x})}[\log p_\theta(\boldsymbol{x}|\boldsymbol{z})] - \beta \cdot \mathrm{KL}(q_\phi(\boldsymbol{z}|\boldsymbol{x})||p(\boldsymbol{z})) \tag{4}$$

[2] Irina Higgins et al. "beta-VAE: Learning basic visual concepts with a constrained variational framework". In: *Proceedings of the International Conference on Learning Representations*. 2016.

Deconstructing the β-VAE — Entropy Regulariser

Theorem 1

$\mathcal{L}_\beta(\boldsymbol{x})$ can be interpreted in terms of the standard ELBO for an adjusted target $\pi_{\theta,\beta}(\boldsymbol{x},\boldsymbol{z}) \triangleq p_\theta(\boldsymbol{x} \mid \boldsymbol{z}) f_\beta(\boldsymbol{z})$ with annealed prior $f_\beta(\boldsymbol{z}) \triangleq p(\boldsymbol{z})^\beta / F_\beta$

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It places no direct pressure on the latents to be independent!

Deconstructing the β-VAE — Rotational Invariance

Theorem 2

If $p(\boldsymbol{z}) = \mathcal{N}(\boldsymbol{z}; 0, \sigma I)$ *and* $q_\phi(\boldsymbol{z} \mid \boldsymbol{x}) = \mathcal{N}\left(\boldsymbol{z}; \mu_\phi(\boldsymbol{x}), S_\phi(\boldsymbol{x})\right)$*, then for all rotation matrices* R*,*

$$\mathcal{L}_\beta(\boldsymbol{x}; \theta, \phi) = \mathcal{L}_\beta(\boldsymbol{x}; \theta^\dagger(R), \phi^\dagger(R))$$

where $\theta^\dagger(R)$ *and* $\phi^\dagger(R)$ *are transformed networks such that*

$$\begin{aligned} p_{\theta^\dagger}(\boldsymbol{x} \mid \boldsymbol{z}) &= p_\theta\left(\boldsymbol{x} \mid R^T \boldsymbol{z}\right), \\ q_{\phi^\dagger}(\boldsymbol{z}|\boldsymbol{x}) &= \mathcal{N}\left(\boldsymbol{z}; R\mu_\phi(\boldsymbol{x}), RS_\phi(\boldsymbol{x})R^T\right). \end{aligned}$$

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The β-VAE does not directly encourage meaningful representations when $p(\boldsymbol{z}) = \mathcal{N}(\boldsymbol{z}; 0, \sigma I)$

Decomposition: Objective

$$\mathcal{L}_{\alpha,\beta}(\boldsymbol{x}) = \mathbb{E}_{q_\phi(\boldsymbol{z}|\boldsymbol{x})}[\log p_\theta(\boldsymbol{x} \mid \boldsymbol{z})] \qquad \text{Reconstruct observations}$$

$$- \beta \cdot \mathrm{KL}(q_\phi(\boldsymbol{z} \mid \boldsymbol{x}) \,\|\, p(\boldsymbol{z})) \qquad \text{Control level of overlap}$$

$$- \alpha \cdot \mathbb{D}(q_\phi(\boldsymbol{z}), p(\boldsymbol{z})) \qquad \text{Impose desired structure}$$

Decomposition: Generalising Disentanglement

Independence: $p(z) = \mathcal{N}(\mathbf{0}, \sigma^\star)$

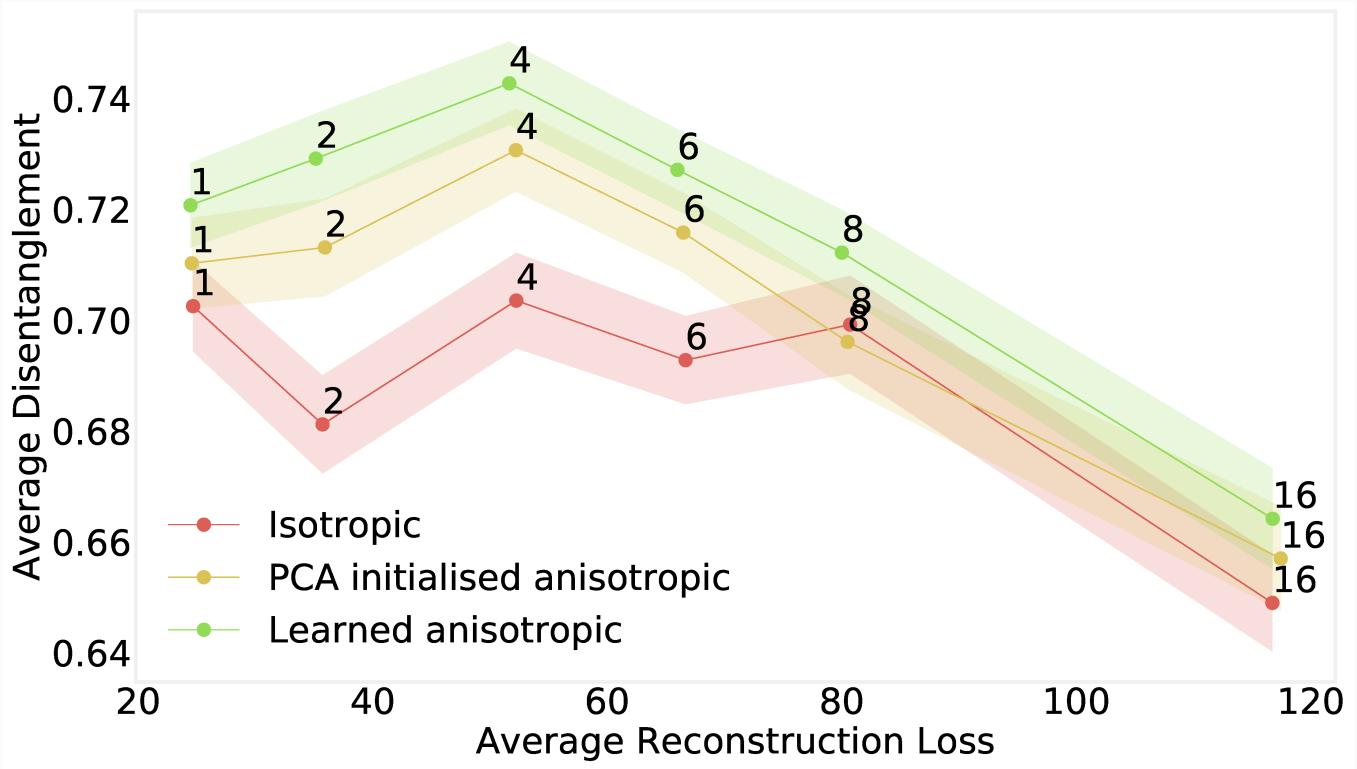

Figure 1: β-VAE trained on *2D Shapes*[3] computing disentanglement[4].

[3] Loic Matthey et al. *dSprites: Disentanglement testing Sprites dataset.* https://github.com/deepmind/dsprites-dataset/. 2017.

[4] Kim and Mnih, "Disentangling by Factorising".

Decomposition: Generalising Disentanglement

Clustering: $p(\boldsymbol{z}) = \sum_{k=1}^{4} \rho_k \cdot \mathcal{N}(\boldsymbol{\mu}_k, \boldsymbol{\sigma}_k)$

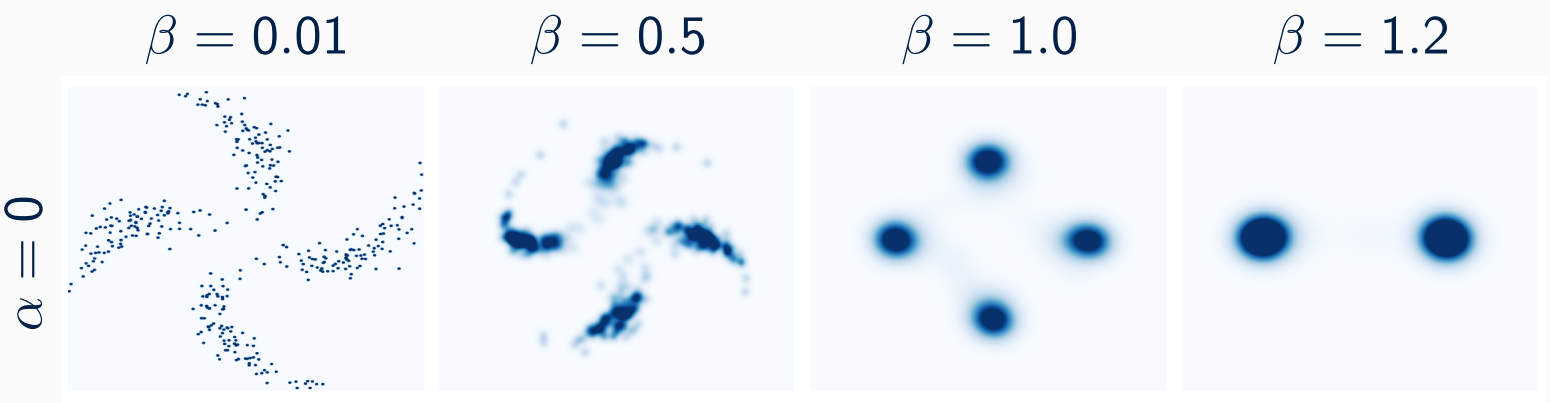

Figure 2: Density of aggregate posterior $q_\phi(\boldsymbol{z})$ with different α, β for the pinwheel dataset.[5]

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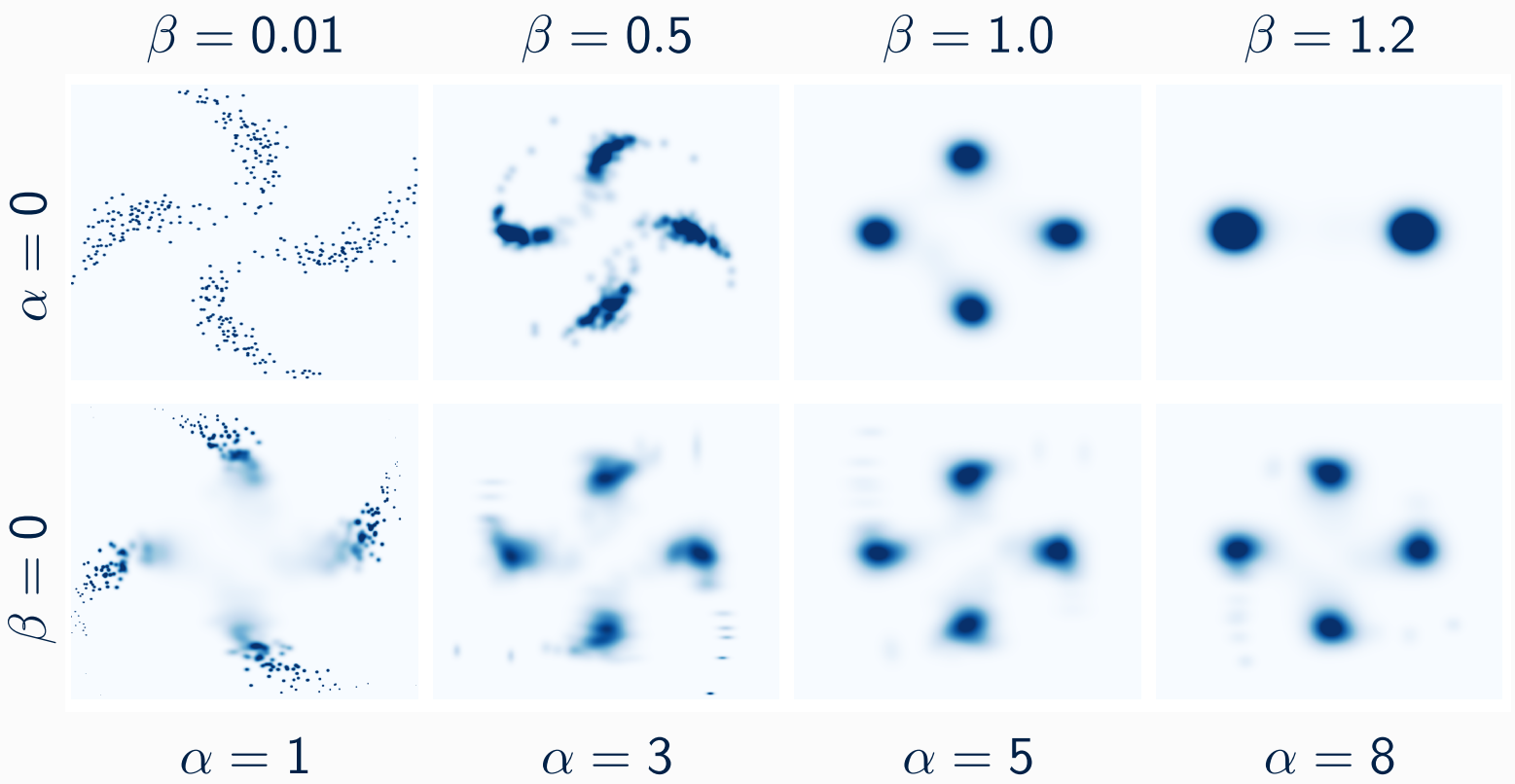

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Sparsity: $p(\boldsymbol{z}) = \prod_d \ (1-\gamma) \cdot \mathcal{N}(\boldsymbol{z}_d; 0, 1) + \gamma \cdot \mathcal{N}(\boldsymbol{z}_d; 0, \sigma_0^2)$

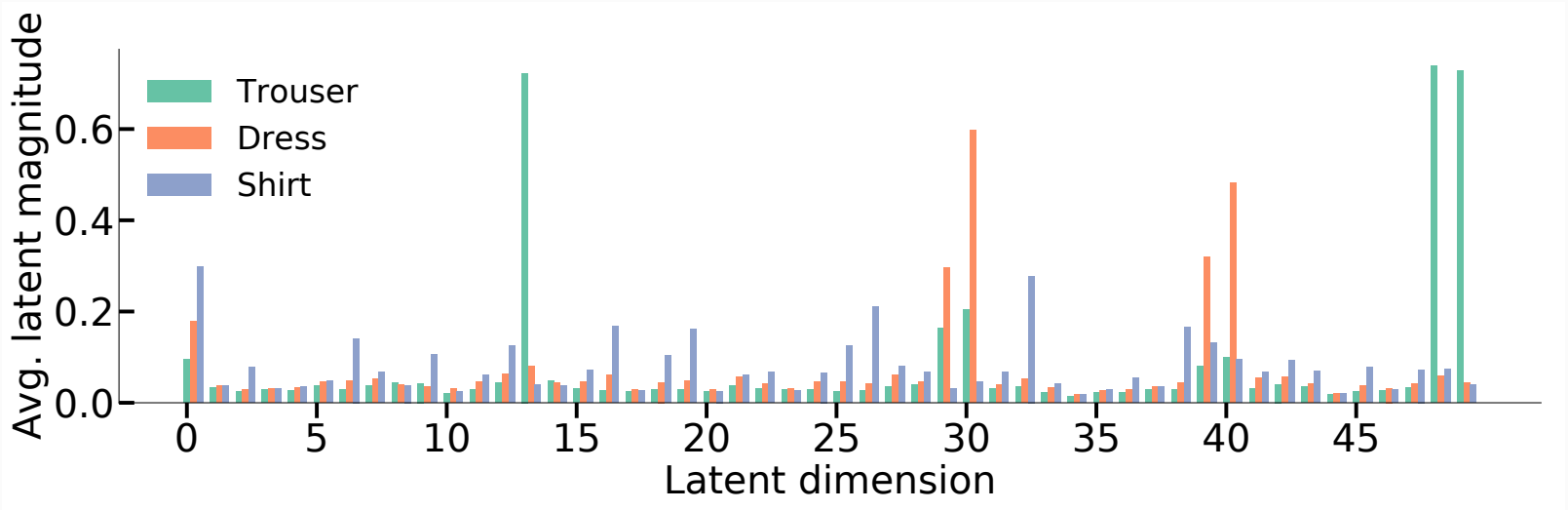

Figure 3: Sparsity of learnt representations for the *Fashion-MNIST*[6] dataset.

[6] Han Xiao, Kashif Rasul, and Roland Vollgraf. *Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms*. Aug. 28, 2017. arXiv: cs.LG/1708.07747 [cs.LG].

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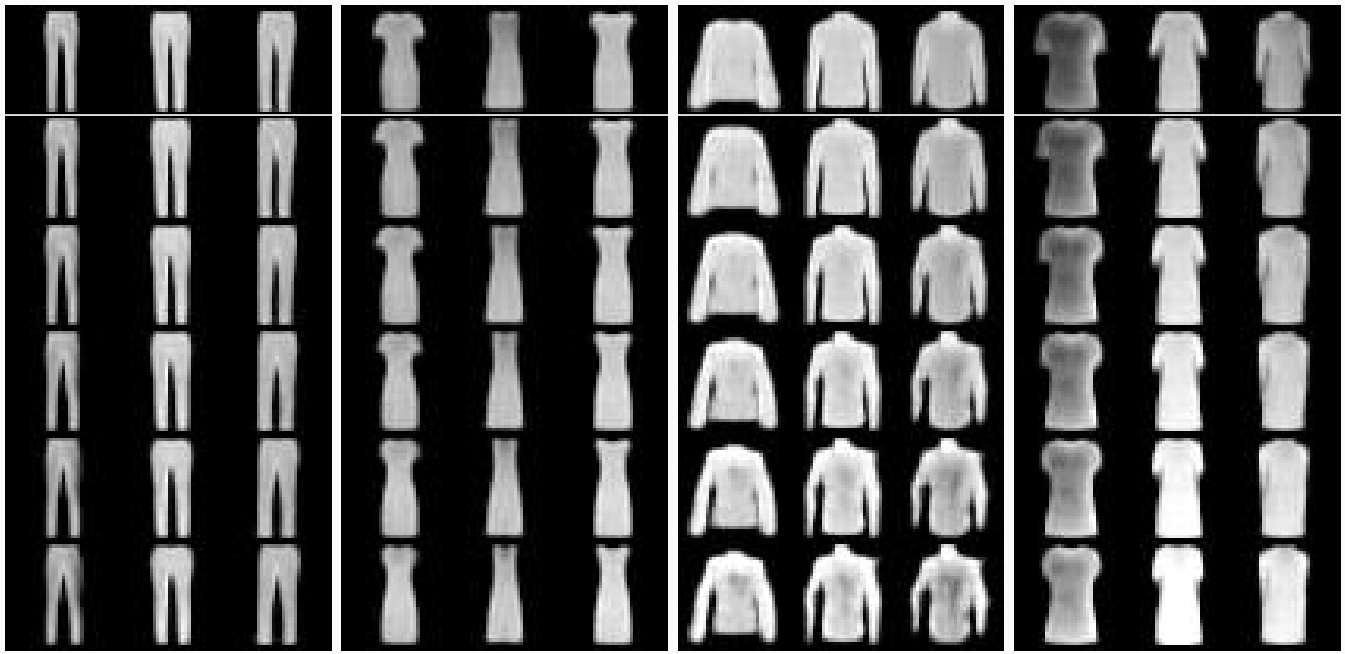

(a) $d = 49$ leg separation

(b) $d = 30$ dress width

(c) $d = 19$ shirt fit

(d) $d = 40$ sleeve style

Figure 3: Latent space traversals for "active" dimensions[6].

[6] Xiao, Rasul, and Vollgraf, *Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms*.

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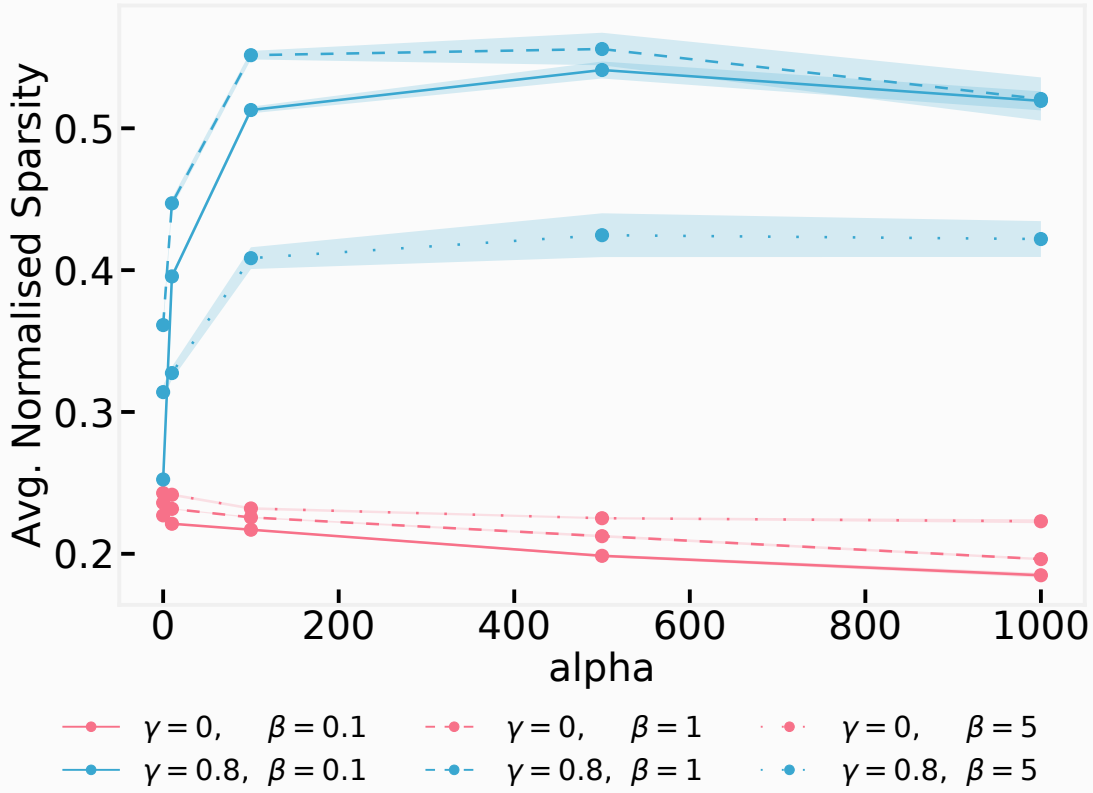

Figure 3: Sparsity vs regularisation strength α (higher better)[6].

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- Experiments that showcase efficacy at different decompositions:
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- $I(\boldsymbol{x}; \boldsymbol{z})$ does not distinguish between large overlap with a small number of datapoints and small overlap with a large number
- It can also fail to account for *locality* in the latent space

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Can VAEs Uncover True Generative Factors?

[7] Francesco Locatello et al. "Challenging Common Assumptions in the Unsupervised Learning of Disentangled Representations". In: *International Conference on Machine Learning* (2019).

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- This fails to account for the stochasticity of the encoder so do not directly apply to VAEs

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Can VAEs Uncover True Generative Factors?

- Empirically this is well known to be very difficult
- Locatello et al. (2019)[7] suggest unsupervised disentanglement is impossible without inductive biases due to equivalence classes in the generative model
- This fails to account for the stochasticity of the encoder so do not directly apply to VAEs
- When, and to what extent, can we expect learned representations to mimic the true generative process?

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- Should disentanglement/decomposition metrics include any notion of a true generative process?

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Code

Paper

iffsid/disentangling-disentanglement

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