# Disentangling Disentanglement in Variational Autoencoders 

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Emile Mathieu*, Tom Rainforth*, N. Siddharth*, Yee Whye Teh June 12, 2019

Departments of Statistics and Engineering Science, University of Oxford

## Variational Autoencoders



## Disentanglement



## Disentanglement = Independence



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


## Decomposition: A Generalization of Disentanglement

Characterise decomposition as the fulfilment of two factors:
(a) level of overlap between encodings in the latent space,
(b) matching between the marginal posterior $q_{\phi}(z)$ and structured prior $p(z)$ to constrain with the required decomposition.

## Decomposition: An Analysis

## Desired Structure

$$
p(\mathbf{z})
$$

## Decomposition: An Analysis

Insufficient Overlap


## Decomposition: An Analysis

## Too Much Overlap



## Decomposition: An Analysis

Appropriate Overlap


## Overlap - Deconstructing the $\beta$-VAE

$$
\begin{aligned}
\mathcal{L}_{\beta}(x) & =\mathbb{E}_{q_{\phi}(z \mid x)}\left[\log p_{\theta}(x \mid z)\right]-\beta \cdot \operatorname{KL}\left(q_{\phi}(z \mid x)| | p(z)\right) \\
& =\underbrace{\mathcal{L}(x)\left(\pi_{\theta, \beta}, q_{\phi}\right)}_{\text {ELBO with } \beta \text {-annealed prior }}+\underbrace{(\beta-1) \cdot H_{q_{\phi}}}_{\text {maxent }}+\underbrace{\log F_{\beta}}_{\text {constant }}
\end{aligned}
$$

## Implications

$\beta$-VAE disentangles largely by controlling the level of overlap It places no direct pressure on the latents to be independent!

## Decomposition: Objective

$$
\begin{aligned}
\mathcal{L}_{\alpha, \beta}(x)= & \mathbb{E}_{q_{\phi}(z \mid x)}\left[\log p_{\theta}(x \mid z)\right] \\
& -\beta \cdot \operatorname{KL}\left(q_{\phi}(z \mid x) \| p( \right. \\
& -\alpha \cdot \mathbb{D}\left(q_{\phi}(z), p(z)\right)
\end{aligned}
$$

$$
-\beta \cdot \operatorname{KL}\left(q_{\phi}(z \mid x) \| p(z)\right) \quad \text { Control Level of overlap }
$$

## Decomposition: Generalising Disentanglement

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



Figure 1: $\beta$-VAE trained on 2D Shapes ${ }^{1}$ computing disentanglement ${ }^{2}$.

[^0]
## Decomposition: Generalising Disentanglement

Clustering: $p(z)=\sum_{k} \rho_{k} \cdot \mathcal{N}\left(\boldsymbol{\mu}_{k}, \boldsymbol{\sigma}_{k}\right)$

$$
\beta=0.01 \quad \beta=0.5 \quad \beta=1.0 \quad \beta=1.2
$$



Figure 2: Density of aggregate posterior $q_{\phi}(z)$ with different $\alpha, \beta$ for the pinwheel dataset. ${ }^{3}$

[^1]
## Decomposition: Generalising Disentanglement

Sparsity: $p(z)=\Pi_{d}(1-\gamma) \cdot \mathcal{N}\left(z_{d} ; 0,1\right)+\gamma \cdot \mathcal{N}\left(z_{d} ; 0, \sigma_{0}^{2}\right)$


Figure 3: Sparsity of learnt representations for the Fashion-MNIST ${ }^{4}$ dataset.

[^2]
## Decomposition: Generalising Disentanglement

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$$
\text { (a) } d=49
$$

leg separation
Figure 3: Latent space traversals for "active" dimensions".

[^3]
## Decomposition: Generalising Disentanglement

Sparsity: $p(z)=\Pi_{d}(1-\gamma) \cdot \mathcal{N}\left(z_{d} ; 0,1\right)+\gamma \cdot \mathcal{N}\left(z_{d} ; 0, \sigma_{0}^{2}\right)$


Figure 3: Sparsity vs regularisation strength $\alpha$ (higher better) ${ }^{4}$.

[^4]
## Recap

We propose and develop:

- Decomposition: a generalisation of disentanglement involving:
(a) overlap of latent encodings
(b) match between $q_{\phi}(\mathbf{z})$ and $p(z)$
- A theoretical analysis of the $\beta$-VAE objective showing it primarily only contributes to overlap.
- An objective that incorporates both factors (a) and (b).
- Experiments that showcase efficacy at different decompositions:
- independence •clustering • sparsity


Emile Mathieu


Tom Rainforth

N. Siddharth Yee Whye Teh

## Code



## Paper


iffsid/disentangling-disentanglement
arXiv:1812.02833

Come talk to us at our poster: \#5


[^0]:    ${ }^{1}$ Matthey et al., dSprites: Disentanglement testing Sprites dataset, p. 1.
    ${ }^{2}$ Kim and Mnih, "Disentangling by Factorising", p. 2.

[^1]:    ${ }^{3}$ http://hips.seas.harvard.edu/content/synthetic-pinwheel-data-matlab.

[^2]:    ${ }^{4}$ Xiao, Rasul, and Vollgraf, Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms.

[^3]:    ${ }^{4}$ Xiao, Rasul, and Vollgraf, Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms.

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