Towards Disentangled Representations via Variational Sparse Coding

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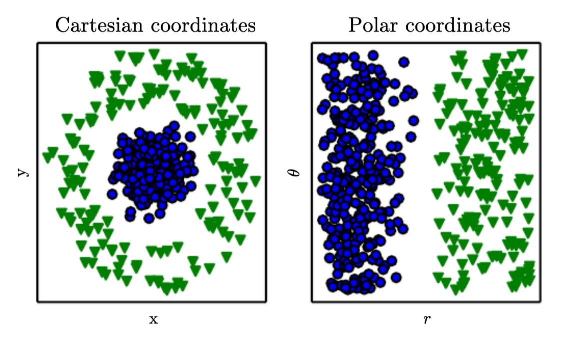
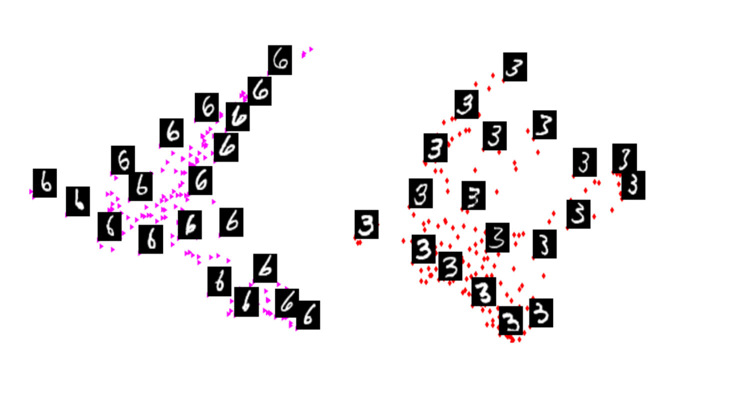
Motivation

Representation Learning

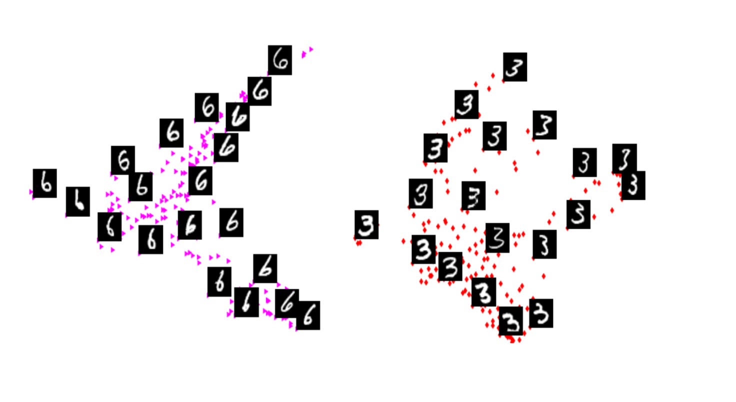


- Simple machine learning algorithms depend *heavily* on the representation of the data they are given.
- The process of designing the right representation for a specific task is commonly known as **feature engineering**.
- An alternative to hand-design these representations is to **learn** them automatically.

Representation Learning



- **Lower dimensional representation** of raw data (images, text, etc).
- **Efficiently sample** from a high-dimensional data distribution.
- Latent space with **meaningful** properties.



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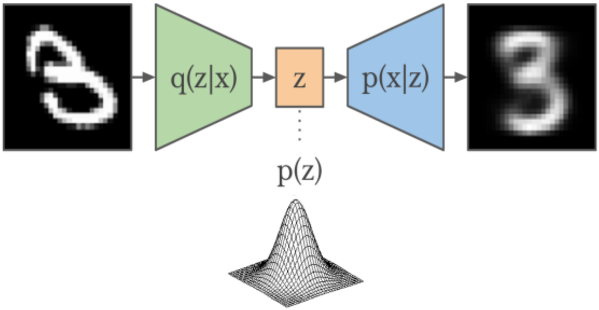
$\rightarrow$ Generative Models to the rescue!

Variational AutoEncoders (VAE)

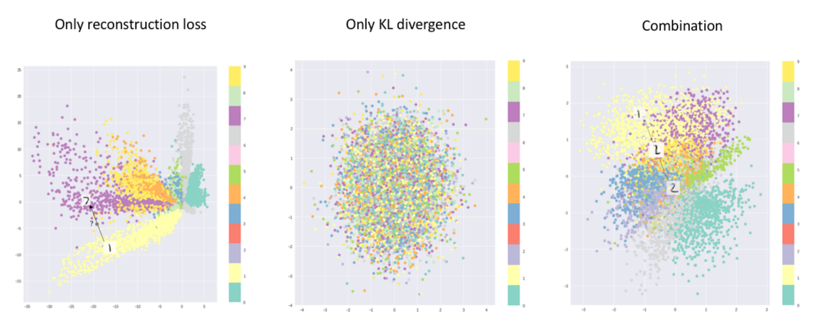
Proposed by Kingma & Welling (2013) and Rezende et al. (2014)

$$\mathcal{L}(\theta, \phi) = \mathbb{E}_{q_\phi(z|x)}\left[\log p_\theta(x|z)\right] - \mathbb{KL}\left(q_\phi(z|x) \| p(z)\right) \qquad (1)$$

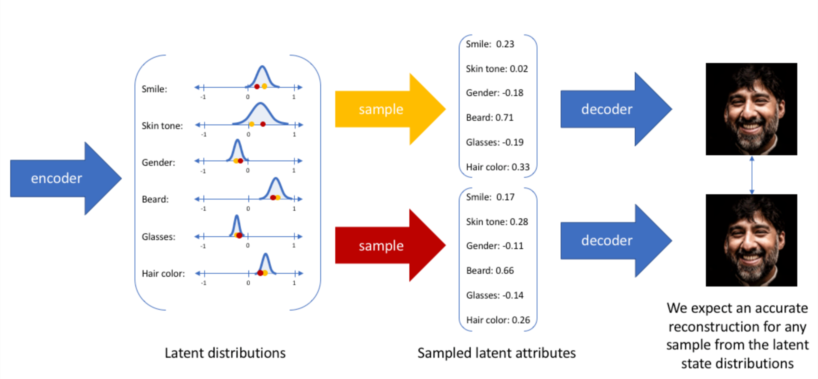


How **expressive** *can a Gaussian latent prior distribution be?*

Both the reconstruction loss and the KL divergence are necessary to produce a *smooth* latent representation of the data.

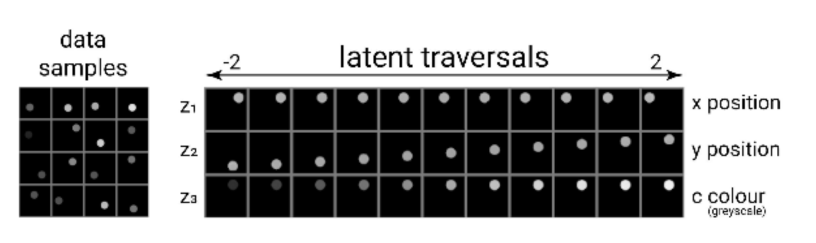


VAE latent codes distribution



Disentanglement

Constitutes the *complex* task of learning representations that separate the **underlying structure** of the world into **disjoint parts of its representation**.

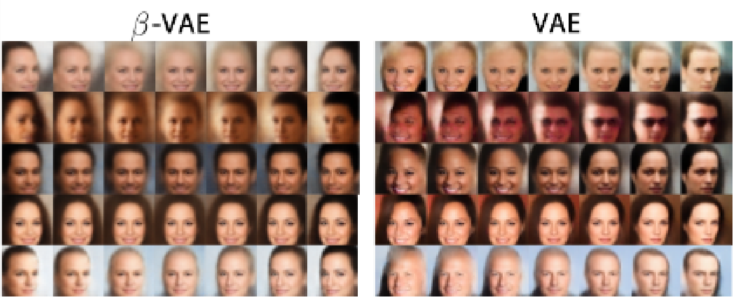


Scheme from the paper “Towards a Definition of Disentangled Representations” by Higgins et al. (2018)

β - VAE

Proposed by Higgins et al. (2017) as a constrained version of VAE to discover disentangled latent factors.

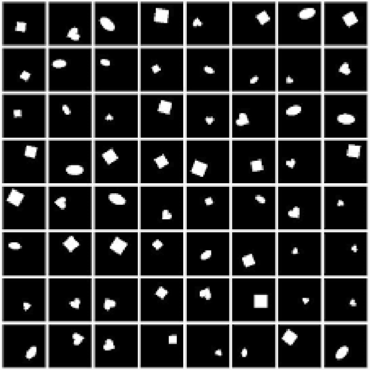
$$\mathcal{L}_{\text{Beta}}(\theta, \phi) = \mathbb{E}_{q_\phi(z|x)}\left[\log p_\theta(x|z)\right] - \beta \, \mathbb{KL}\left(q_\phi(z|x) \| p(z)\right) \tag{2}$$



Azimuth(orientation) traversal comparison.

dSprites Dataset

Created by Matthey et al. (2017) as a way to assess the disentanglement properties of unsupervised learning methods. These 2D shapes were procedurally generated from 6 ground truth independent latent factors: color, shape, scale, rotation, x and y positions of a sprite.



Research Problem

Learning Disentangled Representations

We aim to tackle the following challenges:

- Meaningful low-dimensional representations of images

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- Meaningful low-dimensional representations of images
- Interpretable and disentangled features on latent space.
- Quantitatively and qualitative evaluation of disentanglement.

Technical Contribution

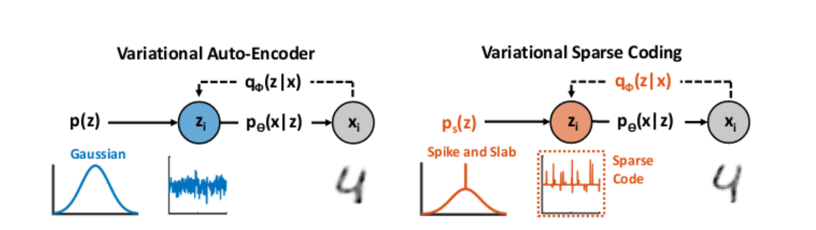
Variational Sparse Coding (VSC)

Tonolini et al. (2019) suggest the use of a **Spike-and-Slab** prior $p(z)$.

$$p_s(z) = \prod_{j=1}^{J} \left(\alpha \mathcal{N}(z_j; 0, 1) + (1 - \alpha)\delta(z_j)\right) \tag{3}$$

which leads to a recognition function as a discrete mixture model,

$$q_\phi(z|x_i) = \prod_{j=1}^{J} \left(\gamma_{i,j}\, \mathcal{N}(z_{i,j}; \mu_{z,i,j}, \sigma^2_{z,i,j}) + (1 - \gamma_{i,j})\delta(z_{i,j})\right) \tag{4}$$



The model captures subjectively understandable sources of variation.

Convolutional encoder/decoder

A convolutional architecture was used for the encoder/decoder of the VAE and VSC for comparison, based on the configuration used by Higgins et al. (2017).

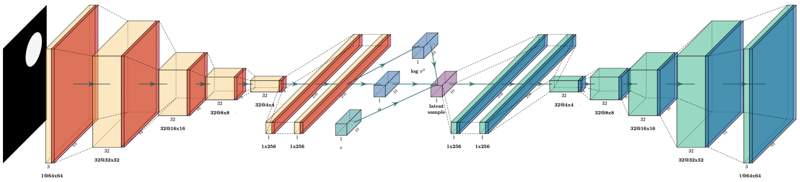


Figure 1: Convolutional architecture used for VAE and VSC

Current Results

Latent Codes Comparison

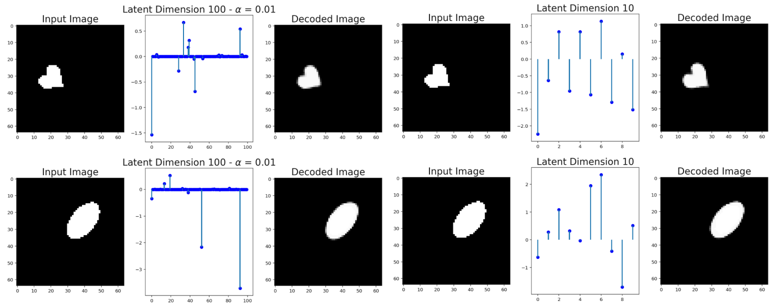


Figure 2: Reconstruction and latent codes of Convolutional VSC (left) ($\alpha = 0.01$, $\beta = 2$) and Convolutional VAE (right) ($\beta = 2$) models with the dSprites dataset.

Latent Space Traversal via VSC

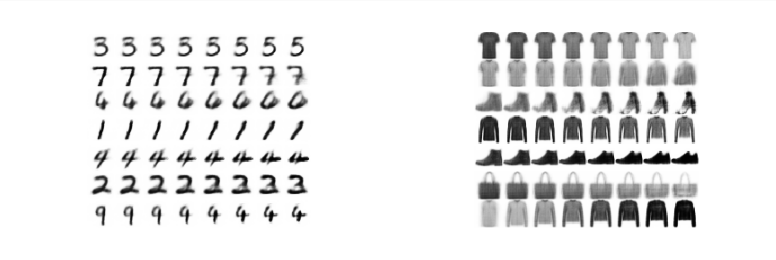


Figure 3: Latent traversals on MNIST (left) and Fashion-MNIST (right).

Latent Space Traversal via VSC

Figure 4: Latent traversals on CelebA (left) and dSprites (right).

Latent Space Traversal Comparison

Figure 5: Latent traversals using the Convolutional VSC (left) and Convolutional VAE (right) models with the dSprites and CelebA datasets.

Next Steps

Disentanglement Metrics and Models

The quantitative evaluation of disentanglement is a recent area of research, with several metrics being constantly proposed, in addition to new models and datasets:

- **Metrics:** BetaVAE score, FactorVAE score, Mutual Information Gap, SAP score, DCI, MCE, IRS
- **Models:** BetaVAE, FactorVAE, BetaTCVAE, DIP-VAE, InfoGAN
- **Datasets:** dSprites, Color/Noisy/Scream-dSprites, SmallNORB, Cars3D, Shapes3D

Next Steps

- Perform quantitative disentanglement evaluation with previously proposed metrics.

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- Extend comparison with recent models also proposed for disentanglement, both VAE-based and GAN-based.
- Perform ablation studies for key features of the model, such as the sparse prior, β-VAE regularization and encoder/decoder used.

Thank you!

Our source code and experiments are available at:

`github.com/Alfo5123/Variational-Sparse-Coding`

See you at the poster session!

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