Learning Disentangled Joint Continuous and Discrete Representations

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● What is this about?

A proposal of Unsupervised Disentangled Representation(UDR) method that can learn both continuous and discrete representations. To do this, they use a relaxed discrete distribution for prior and also control the amount of information encoded in each latent variable.

● What's better than previous works?

While β-VAE (and other works of UDR) can only learn continuous variables, this work can learn both discrete and continuous variables.

● What's the key technique?

In the proposed method, they split the latent variables in to two parts: continuous variables $\mathbf{z}$ and discrete variables $\mathbf{c}$ and use loss function (similar to β-VAE with capacity)

$$\mathcal{L}(\theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z},\mathbf{c}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z},\mathbf{c})] - \gamma|D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})\|p(\mathbf{z})) - C_z| - \gamma|D_{KL}(q\phi(\mathbf{c}|\mathbf{x})\|p(\mathbf{c})) - C_c|$$

For discrete variables, they use a product of independent Gumbel Softmax distributions to parameterize $q(\mathbf{c}|\mathbf{x})$ and used Gumbel Max trick to sample from it. In the equation below, $\mathbf{y}$ is continuous approximation of $\mathbf{c}$:

$$y_k = \frac{\exp((\log \alpha_k + g_k)/\tau)}{\sum_i \exp((\log \alpha_i + g_i)/\tau)} \quad g_k \sim \mathrm{Gumbel}(0,1) \quad \tau : \text{temperature}$$

● How did they evaluate that?

Qualititative evaluation with MNIST, FashionMNIST, CelebA, Chairs using latent traversal + Quantitative evaluation with dSprites using β-VAE score.

● Any discussions & insights?

The proposed method outperforms previous works when a discrete generative factor is prominent.

● Which paper to read next?

Esmaeili, Babak, et al. "Structured disentangled representations." *The 22nd International Conference on Artificial Intelligence and Statistics*. PMLR, 2019.