Learning Latent Subspaces in Variational Autoencoders

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Vanilla VAE

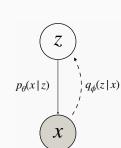
VAE framework-Marrying PGM and Deep learning

- · x high dimensional
- Goal: sample from $p^*(\mathbf{x})$, get $p^*(z|\mathbf{x})$ (and z?)
- · Parameterization with NN:

$$p^*(\mathbf{x}|\mathbf{z}) \approx p_{\theta}(\mathbf{x}|\mathbf{z}) = \mathcal{D}(\mathbf{x}; \theta(\mathbf{z}))$$
$$p^*(\mathbf{z}|\mathbf{x}) \approx q_{\phi}(\mathbf{z}; \mathbf{x}) = \mathcal{N}(\mathbf{z}; \mu_{\phi}(\mathbf{x}), \sigma_{\phi}(\mathbf{x})l)$$

· Optimizing the ELBO:

$$\begin{split} \log p_{\theta}(\mathbf{x}) &= \mathcal{L}_{\theta,\phi}(\mathbf{x}) + \mathcal{D}_{\mathsf{KL}}(q_{\phi}(\mathbf{z} \mid \mathbf{x}) \mid\mid p_{\theta}(\mathbf{z} \mid \mathbf{x})) \\ &\geq \mathsf{E}_{q_{\phi}(\mathbf{z} \mid \mathbf{x})}[\log p_{\theta}(\mathbf{x} \mid \mathbf{z})] - \mathcal{D}_{\mathsf{KL}}(q_{\phi}(\mathbf{z} \mid \mathbf{x}) \mid\mid p_{\theta}(\mathbf{z})) \end{split}$$



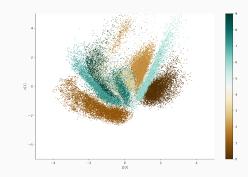
VAE-Demo

on Google colab, Tf 2.0

https://colab.research.google.com/drive/12_9dp3yJF6U_FM8CY980905SIcDNMdV1?usp=sharing

VAE latent space-common pitfalls

- Interpretation of *z*?
- Dimension of z?
- · How to navigate z?





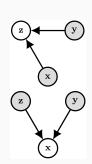
Conditional VAE

conditional VAE

- · Conditioning on label y
- Objective:

$$\textit{E}_{\textit{q}_{\phi}(\textbf{z}|\textbf{x},\textbf{y})}[\log \textit{p}_{\theta}(\textbf{x}\mid\textbf{z},\textbf{y})] - \mathcal{D}_{\textit{KL}}(\textit{q}_{\phi}(\textbf{z}\mid\textbf{x},\textbf{y}) \mid\mid \textit{p}_{\theta}(\textbf{z},\textbf{y}))$$

- · Manipulate and control data
- · Interpretable structure?



cVAE-Demo

on Google colab, Tf 2.0

https://colab.research.google.com/drive/
1Cupg-5DS0GUikwJ0atEuMiZZPptiM0bI?usp=sharing