

# Learning Hierarchical Features with Joint Latent Space Energy-Based Prior

Jiali Cui<sup>1</sup>   Ying Nian Wu<sup>2</sup>   Tian Han<sup>1</sup>

<sup>1</sup>Stevens Institute of Technology

<sup>2</sup>University of California, Los Angeles (UCLA)

September 21, 2023



# Multi-layer Generator Model

- **Generator Model** can be specified using joint distribution:

$$p_{\beta}(\mathbf{x}, \mathbf{z}) = p_{\beta_0}(\mathbf{x}|\mathbf{z})p_{\beta_{>0}}(\mathbf{z})$$

- **Multi-layer Generator Model** consists of multiple layers of latent variables:

$$p_{\beta_{>0}}(\mathbf{z}) = \prod_{i=1}^{L-1} p_{\beta_i}(\mathbf{z}_i|\mathbf{z}_{i+1})p(\mathbf{z}_L)$$

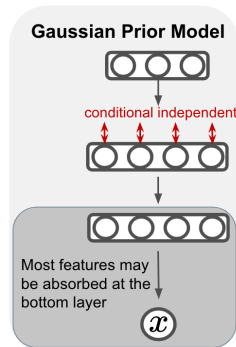
- Conditional Gaussian Distribution

$$p_{\beta_i}(\mathbf{z}_i|\mathbf{z}_{i+1}) \sim \mathcal{N}(\mu_{\beta_i}(\mathbf{z}_{i+1}), V_{\beta_i}(\mathbf{z}_{i+1}))$$

# Hierarchical Representation Learning

## Limitation

- ① Such multi-layer generator models can learn most data representation at the bottom layer.
- ② Intra-layer relation among latent units is ignored.
- ③ conditional independent



# Hierarchical Representation Learning

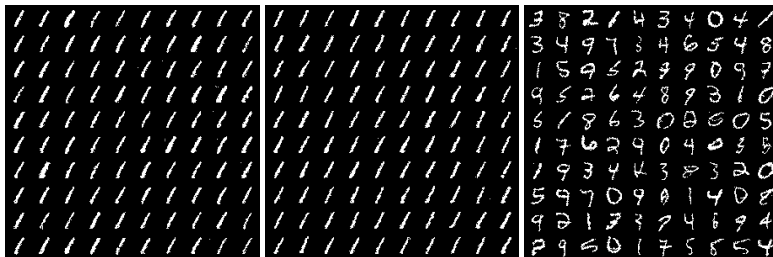


Figure: Hierarchical Sampling.

# Latent Space Energy-based Model

- Latent space energy-based model (EBM) can be specified as:

$$p_{\alpha}(\mathbf{z}) = \frac{1}{Z(\alpha)} \exp[f_{\alpha}(\mathbf{z})] p_0(\mathbf{z})$$

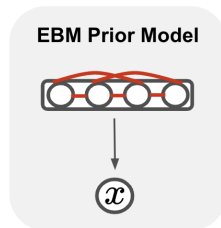
where  $Z(\alpha)$  is the normalizing function,  $f_{\alpha}(\mathbf{z})$  is the energy function, and  $p_0(\mathbf{z})$  is the referenced distribution.

# Hierarchical Representation Learning

## Limitation

- ① Single-layer latent space.
- ② Mixed representation learned.

non-hierarchical structure



# Hierarchical Representation Learning

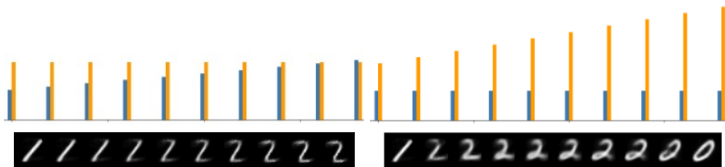


Figure: Latent traverse.

# Joint Latent Space EBM

- Joint Latent Space EBM Prior

$$p_{\alpha}(\mathbf{z}) = \frac{1}{Z(\alpha)} \exp[f_{\alpha}([\mathbf{z}_1, \dots, \mathbf{z}_L])] p_0([\mathbf{z}_1, \dots, \mathbf{z}_L])$$

- Architectural Generation Model

$$h_L = g_L(\mathbf{z}_L)$$

$$h_i = g_i([\mathbf{z}_i, h_{i+1}]), \quad i = 1, 2, \dots, L-1$$

$$\mathbf{x} \sim \mathcal{N}(h_1, \sigma^2 I_D)$$



# Joint Latent Space EBM

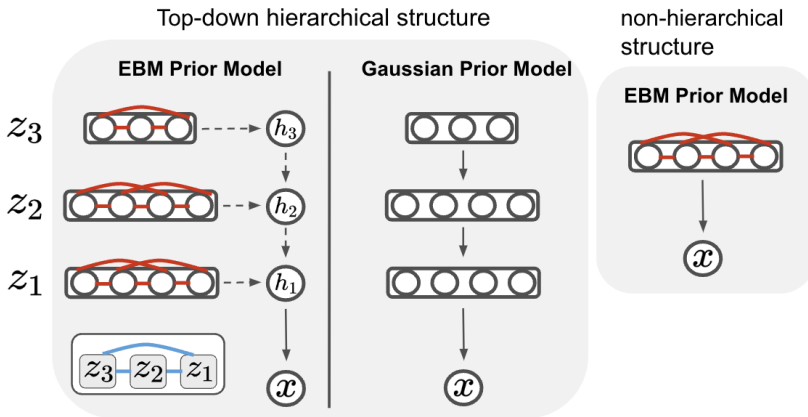


Figure: Illustration.

# Hierarchical Representation Learning

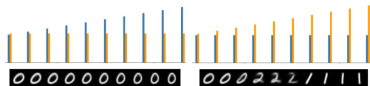


Figure: Latent traverse.



Figure: Hierarchical sampling on MNIST.



Figure: Hierarchical sampling on SVHN.

# Expressivity

Method	SVHN	CelebA-64
ABP	49.71	51.50
LVAE	39.26	53.40
BIVA	31.65	33.58
SRI	35.23	36.84
VLAЕ	43.95	44.05
2s-VAE	42.81	44.40
RAE	40.02	40.95
NCP-VAE	33.23	42.07
Multi-NCP	26.19	35.38
LEBM	29.44	37.87
<b>Ours</b>	24.16	32.15

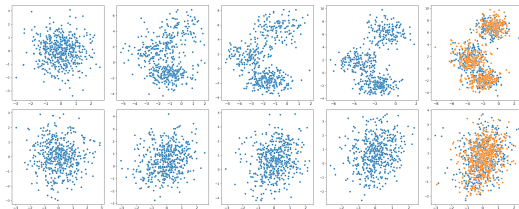


Table: IS( $\uparrow$ ) and FID( $\downarrow$ ) on CIFAR-10.

Figure: Visualization of Latent Space.

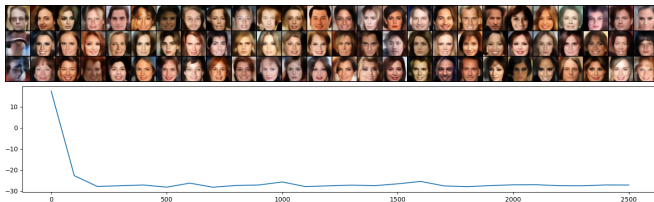


Figure: Long-run Langevin traverse.