

Latent Diffusion Energy-Based Model for Interpretable Text Modeling

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Motivation

Latent Space Energy-Based Model (EBM): Pros and Cons

- + flexibility in the formulation
- + stronger modeling power of the latent space
- requiring MCMC sampling (problematic in practice)

We may leverage **diffusion recovery likelihood learning** as a cure for the MCMC sampling issue!

Modeling: Key ideas

Vanilla Energy-Based Prior

$$p_\alpha(\mathbf{z}) = \frac{1}{Z_\alpha} \exp(F_\alpha(\mathbf{z})) p_0(\mathbf{z}),$$

Latent Diffusion Energy-Based Prior

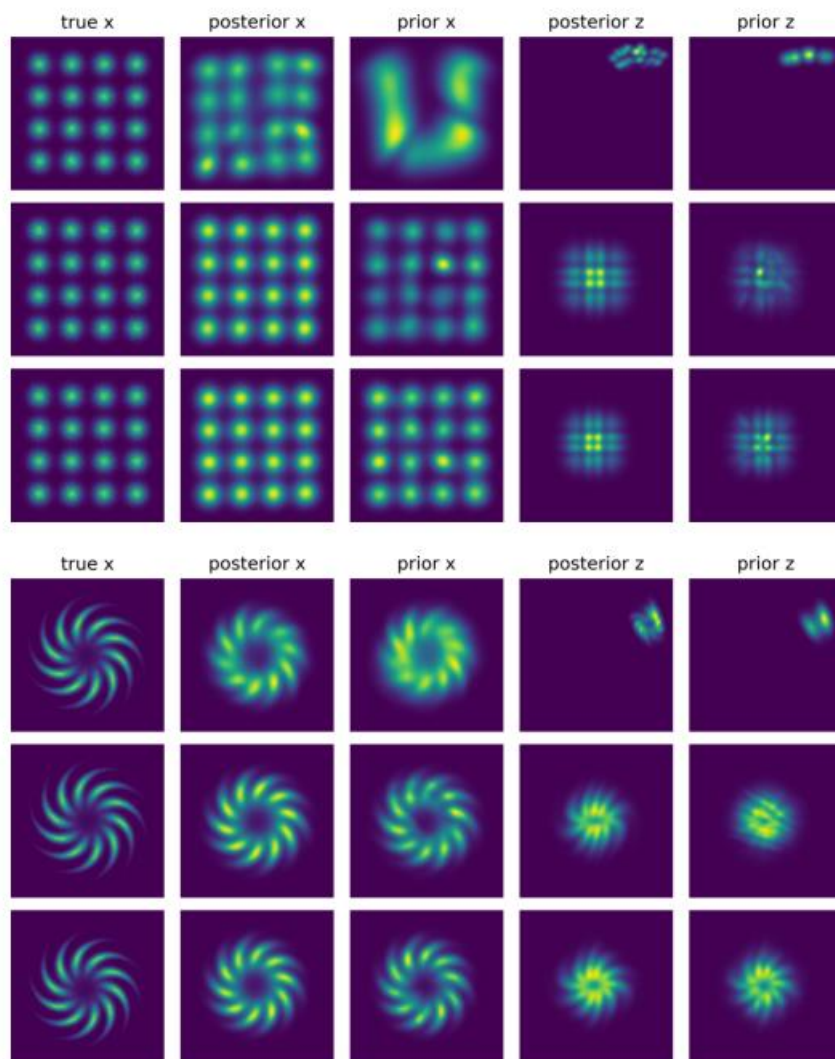
Forward diffusion process

$$q_\phi(\mathbf{z}_{0:T}|\mathbf{x}) = q_\phi(\mathbf{z}_0|\mathbf{x}) \prod_{t=0}^{T-1} q(\mathbf{z}_{t+1}|\mathbf{z}_t);$$
$$q(\mathbf{z}_{t+1}|\mathbf{z}_t) = \mathcal{N}(\mathbf{z}_{t+1}; \sqrt{1 - \sigma_{t+1}^2} \mathbf{z}_t, \sigma_{t+1}^2 \mathbf{I}).$$

Backward diffusion process

$$p_\alpha(\tilde{\mathbf{z}}_t|\mathbf{z}_{t+1}) = \frac{1}{\tilde{Z}_{\alpha,t}(\mathbf{z}_{t+1})} \exp\left(F_\alpha(\tilde{\mathbf{z}}_t, t) - \frac{1}{2\sigma_{t+1}^2} \|\tilde{\mathbf{z}}_t - \mathbf{z}_{t+1}\|^2\right),$$

Results



MODEL	rPPL \downarrow	BLEU \uparrow	wKL \downarrow	NLL \downarrow
TEST SET	-	100.0	0.14	-
RNN-LM	-	-	-	101.21
AE	730.81	10.88	0.58	-
VAE	686.18	3.12	0.50	100.85
DAE	797.17	3.93	0.58	-
DVAE	744.07	1.56	0.55	101.07
DI-VAE	310.29	4.53	0.24	108.90
SEMI-VAE	494.52	2.71	0.43	100.67
SEMI-VAE + \mathcal{I}	260.28	5.08	0.20	107.30
GM-VAE	983.50	2.34	0.72	99.44
GM-VAE + \mathcal{I}	287.07	6.26	0.25	103.16
DGM-VAE	257.68	8.17	0.19	104.26
DGM-VAE + \mathcal{I}	247.37	8.67	0.18	105.73
SVEBM	180.71	9.54	0.17	95.02
SVEBM-IB	177.59	9.47	0.16	94.68
OURS w/o GC	<u>168.32</u>	<u>11.12</u>	<u>0.07</u>	79.84
OURS	164.57	11.16	0.06	<u>82.38</u>

See more results in our paper.

Thanks for your time!