

Learning Probabilistic Models from Generator Latent Spaces with Hat EBM

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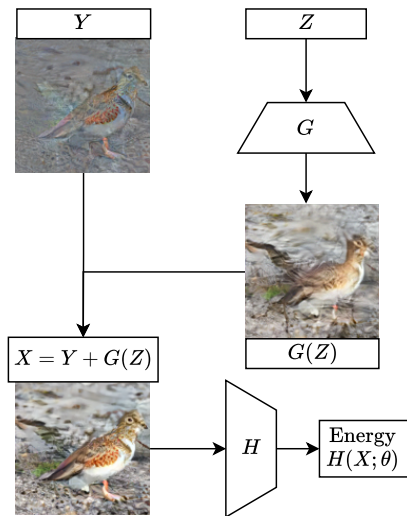
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Hat EBM Introduction



- We propose a method for building an Energy-Based Model (EBM) on top of a generator network, called the **Hat EBM**
- The energy is defined jointly over a latent vector Z and residual image Y
- To get the joint energy, we generate an image $G(Z)$, add the residual Y , and pass the sum through the hat network $H(X; \theta)$

Motivation

- Defining a probability distribution over the output of a generator network is challenging
 - Density change-of-variables is one way, but requires log determinant of generator Jacobian
 - Inferring latent states of observed data is another way (Latent Prior EBMs), but requires MCMC or inference network
- We introduce a residual image to adjust the output of the generator. Formulation bypasses both generator Jacobian and inference of latent states for observations
- Generator learns overall image structure while residuals capture fine-grain details

Joint Energy over Latent and Residual Space

$$p(y, z; \theta) = \frac{1}{\mathcal{Z}(\theta)} \exp\{-H(G(z) + y; \theta)\}$$

Applications: Generator Refinement, EBM with Deterministic Autoencoder

Residual Energy Conditioned on Latent State

$$p(y, z; \theta) = \frac{1}{\mathcal{Z}_z(\theta)} p_0(z) \exp\{-H(G(z) + y; \theta)\}$$

Applications: Image Synthesis, OOD Detection

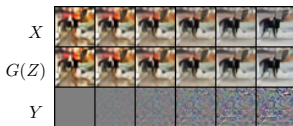
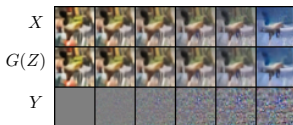
Hat EBM Sampling Paths

Refinement



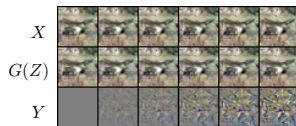
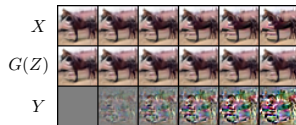
Langevin Steps \rightarrow

Retrofit



Langevin Steps \rightarrow

Synthesis



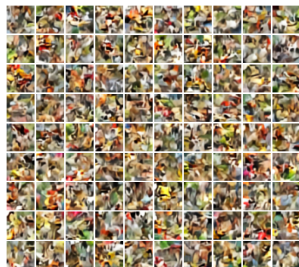
Langevin Steps \rightarrow

Refinement and Retrofit Experiments

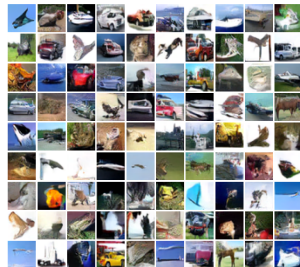
Refining SN-GAN Generators

Model	CIFAR-10 FID	CelebA FID
SN-GAN (baseline)	18.58 ± 0.08	6.13 ± 0.03
DDL5	14.59 ± 0.07	6.06 ± 0.01
Hat EBM	14.04 ± 0.11	5.98 ± 0.02

Hat EBM with Generator from Deterministic Autoencoder



Initial States



Short-Run MCMC Samples
FID 26.01

Hat EBM for Synthesis

CIFAR-10 (32 × 32)

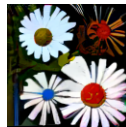
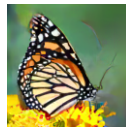
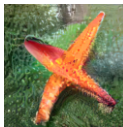
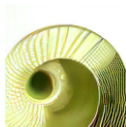
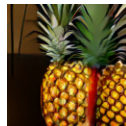
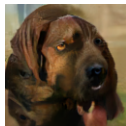
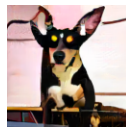
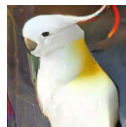
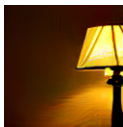
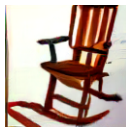
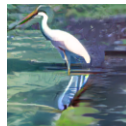
Model	FID
Hat EBM (<i>Ours</i>)	19.30 ± 0.15
Improved CD EBM	25.1
VERA	27.5
Cooperative EBM	33.6
Flow EBM	37.3
JEM	38.4
IGEBM	40.6
DDPM	3.2
NCSNv2	10.9
SN-GAN	18.6

CelebA (64 × 64)

Model	FID
Hat EBM (<i>Ours</i>)	11.57 ± 0.04
Divergence Triangle	31.9
SN-GAN	6.1
NCSNv2	10.2

ImageNet (128 × 128)

Model	FID
Hat EBM (<i>Ours</i>)	40.24 ± 0.18
SN-GAN	65.7
SS-GAN	43.9
InfoMax GAN	58.9
Hat EBM, scaled (<i>Ours</i>)	29.37 ± 0.15
SS-GAN, scaled	23.4



Thank you!

Code and pretrained models available at

<https://github.com/point0bar1/hat-ebm>