Normalizing Flow - Abilities

Compare abilities with other density estimation models

Model classes

Model	Benefits	Drawbacks
GANs	Good samples Fast training & sampling	Likelihood not defined Unstable training
EBMs	Not constrained	Likelihood is intractable Sampling is intractable
VAEs	Fast training & sampling	Likelihood is intractable
ARMs	Exact likelihoods Good likelihoods	Slow sampling
Flows	Exact likelihoods Fast sampling	Constrained architectures
Diffusion	Good likelihoods Good samples	Likelihood is intractable Sampling is slow

Add in easy and straightforward maximum likelihood training!

https://www.youtube.com/watch?v=2tVHbcUP9b8

GANs are not likelihood based models

Author of ADAM optimizer arguing that Normalizing flows should not be judged on their sample quality:

dpkingma · 3 yr. ago
OpenAI

Comparing GANs to likelihood-based generative models is not apples-to-apples, since they are optimized towards different objectives. The objectives present different trade-offs.

For the same parameter budget, GANs can produce much sharper images, since the objective allows the model to assign zero probability to all training points, as long as the samples that are generated look realistic to the discriminator.

Contrary to your typical GAN objective, a fundamental property of the log-likelihood objective is that after training, every training point is likely under the generative model. As long as you don't overfit, which is easy to check against, every new image is also likely under the model (assuming i.i.d. data).

In case of latent-variable models of images such as Glow, this means that the latent space can meaningfully represent new images. This also means that you can do things like manipulations of new images in a latent space. ProGAN and SAGAN won't allow you to do this, at least not without serious modifications.

https://www.reddit.com/r/MachineLearning/comments/99hh5a/r_glow_generative_flow_with_invertible_1x1/