Adversarial Likelihood in feature space

Amortized variational inference is used jointly with Maximum-Likelihood estimation (MLE) and adversarial training. Mode-dropping strongly penalizes MLE but is non-trivial due to conditional independance assumptions. Joint training is richer but non trivial due to conditional independance assumptions.

Ideas:
- Use flow transformations to learn beyond conditional independance in image space
- Use adversarial training together with MLE to control where the off-dataset mass goes

Adversarial training leads \( p_\theta \) to optimise support coverage and penalise over-generalisation. The flow model \( f_\psi \) is assumed less flexible than classical models and can miss modes of low density. Thus, an additional constraint is added to the objective of \( f_\psi \) to avoid low density regions:

\[
\mathcal{L}_{ELBO}(x, \theta, \psi) = \mathbb{E}_{q_\theta(z|x)} \left[ \ln p_\theta(f_\psi(z)|x) \right] - D_{KL}(q_\theta(z|x) || p_\theta(z)) \leq \ln p_\theta(f_\psi(x)).
\]

Adversarial training with Adaptive Density Estimation: Sample from \( p_\theta \) in feature space, obtain image samples with \( f_\psi^{-1} \) and evaluate with a discriminator \( D \):

\[
\mathcal{L}_Q(p_\nu, \psi) = -\mathbb{E}_{z \sim p_\nu(z)} \left[ \ln D(f_\psi^{-1}(\mu_\nu(z))) - \ln(1 - D(f_\psi^{-1}(\mu_\nu(z)))) \right].
\]

Ideal loss: Under discriminator optimality assumption, optimises a lower bound on the symmetric Kullback-Leibler divergence:

\[
\mathcal{L}_C(p_\nu, \psi) = \mathbb{E}_{x \sim p_\nu} \left[ \ln D(f_\psi^{-1}(\mu_\nu(z))) - \ln(1 - D(f_\psi^{-1}(\mu_\nu(z)))) \right] + D_{KL}(p_\nu || p_\psi) + D_{KL}(p_\nu || p_\psi).
\]

Adversarial BPD

FlowGan(A)

4.4 5.1 58.6

FlowGan(H)

4.2 3.9

Ours

4.4 5.1 58.6

Ours

3.9 7.1 28.0

FlowGAN(5)

5.8

FlowGAN(10)

5.5

SNGan

5.9

SNGan(5)

5.8

SNGan(10)

7.0

Glow

5.5

SOTA comparison on CIFAR-10