

CSDS 600: Deep Generative Models

Homework 2

Instructor: Yu Yin

Due Date: **11:59 pm Oct. 15**

Submission: Canvas

1. Normalizing Flows (20/100)

- Describe the training objective for flows.
- Describe the sampling process of normalizing flows.
- What properties does the transformation function f_θ must satisfy for practical flow models?

2. Wasserstein Distance (35/100)

In many cases, the GAN algorithm can be thought of as minimizing a divergence between a data distribution p_{data} and the model distribution p_g . In this problem, we will explore an issue with various divergences (e.g., Jensen-Shannon divergence and KL divergence) and one potential way to fix it.

- Let $p_{data} \sim \mathcal{N}(\theta_0, \epsilon^2)$ and $p_g \sim \mathcal{N}(x|\theta, \epsilon^2)$ be normal distributions with standard deviation ϵ centered at $\theta_0 \in \mathbb{R}$ and $\theta \in \mathbb{R}$, respectively. Show that

$$D_{KL}(p_g || p_{data}) = \frac{(\theta - \theta_0)^2}{2\epsilon^2}.$$

- Suppose p_{data} and p_g both place probability mass in only a very small part of the domain; that is, consider the limit $\epsilon \rightarrow 0$. What happens to $D_{KL}(p_g || p_{data})$ and its derivative with respect to θ , assuming that $\theta \neq \theta_0$?
- Would this pose an issue for a GAN trained with the loss function defined below? Why?

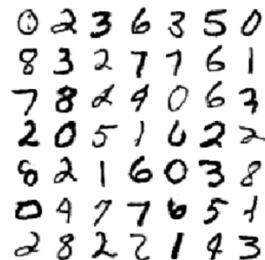
$$L_G(\theta; \phi) = \mathbb{E}_{\mathbf{x} \sim p_\theta(\mathbf{x})}[\log(1 - D_\phi(\mathbf{x}))] - \mathbb{E}_{\mathbf{x} \sim p_\theta(\mathbf{x})}[\log D_\phi(\mathbf{x})]$$

- Under the same circumstances as (b), compare KL divergence, JS divergence and Wasserstein Distance.

3. Wasserstein GAN for MNIST (45/100)

In this question, you will train a Wasserstein GAN on the MNIST dataset, which comprises 28×28 grayscale images.

- Implement the optimization process for the Wasserstein GAN. Consider making multiple updates (e.g., 2) to the discriminator for each update to the generator.
- Train your model for 40 epochs (we recommend using a learning rate of $\text{lr} = 3\text{e-}4$). After training, the generated samples should resemble the results shown below.



0 2 3 6 3 5 0
8 3 2 7 7 6 1
7 8 2 9 0 6 3
2 0 5 1 6 2 2
8 2 1 6 0 3 8
0 4 7 7 6 5 1
2 8 2 2 1 4 3

Request deliverables:

- Provide 100 samples from your trained WGAN.
- Report the Inception Score (https://github.com/openai/improved-gan/tree/master/inception_score).
- Include Interpolations between two random latent variables.