## **Marked exercises, submission 2**

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**2.10.8** [10 points]Challenges with training GANs (200 words max)

*Your answer here.*

Training GANs comes with several challenges, the most significant being "mode collapse." Mode collapse happens when the generator produces a limited variety of outputs, ignoring the diversity of the training data. This occurs if the generator sticks to a few modes that effectively fool the discriminator, resulting in a lack of diversity.

This issue can arise due to several factors. Optimization dynamics can cause the generator to focus on outputs that consistently deceive the discriminator. A too-powerful discriminator can also lead the generator to converge on specific outputs. Additionally, inadequate updates during training may prevent the generator from exploring the full data distribution.

To address these challenges, methods like Wasserstein GANs, which use the Wasserstein loss function, and Unrolled GANs, which consider both current and future discriminator losses, can be employed.

The second problem is the convergence of the different models. As the generator improves, the discriminator's accuracy drops to 50%, effectively guessing randomly. This undermines meaningful feedback for the generator, leading to poor convergence. If training continues, the generator starts learning from random feedback, causing a collapse in the quality of generated outputs. This problem can be partially solved using different methods as: Adding noise to discriminator inputs or Penalizing discriminator weights.

**2.10.9** [10 points] Evaluation metrics for GANs (200 words max)

*Your answer here.*

The Inception Score (IS) is a metric used to assess the quality and diversity of generated images. It measures the KL-divergence between the conditional label distribution given an image and the marginal label distribution over all generated images. This metric is easy to compute using a pre-trained Inception model, offering insights into the quality and diversity of generated samples. It provides an objective measure of GAN performance and is widely used in the literature. However, IS is limited to evaluating image generation tasks and may not apply to other data types. It can also be sensitive to the architecture of the Inception model, impacting the comparability of results, and may not accurately capture mode collapse.

On the other hand, the Fréchet Inception Distance (FID) compares the distribution of real and generated images by computing the Fréchet distance between their feature representations extracted from a pre-trained Inception network. FID offers a robust measure of GAN performance, is less sensitive to changes in data scale, and provides an objective and intuitive measure based on perceptual similarity. However, it is computationally expensive, especially for large datasets, and its performance may vary depending on the quality and architecture of the pre-trained Inception model used. Like IS, FID is primarily designed to evaluate image generation tasks and may not generalize well to other data types.

**References**

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