Assignment 4 - Generative Adversarial Networks

Q1: Explain the minimax loss function in GANs and how it ensures competitive training between the generator and discriminator.
Ans: The minimax loss function in GANs involves a game between the generator (G) and discriminator (D). The generator tries to produce fake data that the discriminator cannot differentiate from real data, while the discriminator attempts to correctly identify whether data is real or fake. This setup creates a competitive dynamic where the generator improves at generating realistic data, and the discriminator gets better at identifying fake data, thus pushing both to improve simultaneously.

Q2: What is mode collapse, why can mode collapse occur during GAN training? And how can it be mitigated.
Ans: Mode collapse occurs when the generator produces limited or repetitive outputs, failing to capture the full diversity of the data. It usually happens when the discriminator becomes too powerful, forcing the generator to create a narrow set of outputs that fool the discriminator.
Mitigation:

- Wasserstein GAN (WGAN): Uses a different loss function based on the Wasserstein distance to reduce instability and mode collapse.
- Minibatch Discrimination: Encourages diversity by penalizing the generator for producing similar outputs in a batch.
- Feature Matching: Encourages the generator to match the statistics of real data to prevent the collapse into a small subset of outputs.

Q3: Explain the role of the discriminator in adversarial training.
Ans: The discriminator in GANs plays a key role in distinguishing between real data (from the actual dataset) and fake data (generated by the generator). It is trained to correctly classify real and fake samples, providing feedback to the generator. During training, as the generator improves and creates more realistic data, the discriminator must become better at identifying fake data. The discriminator's loss function helps evaluate its performance based on its ability to distinguish real and fake data. This feedback is crucial for updating the generator, driving it to produce more realistic outputs. Ultimately, the discriminator's ability to identify fake data guides the generator, pushing both networks to improve through their adversarial relationship.

Q4: How do metrics like IS and FID evaluate GAN performance?
Ans: To assess the performance of GANs, various metrics are used to evaluate the quality and diversity of generated outputs, with Inception Score (IS) and Fréchet Inception Distance (FID) being two commonly used measures.

- Inception Score (IS): Measures both the quality and diversity of generated images. A high IS indicates that images are both realistic and varied, with distinct class labels. However, it assumes the Inception model works well for the dataset.
- Fréchet Inception Distance (FID): Measures the similarity between the real and generated image distributions by comparing their mean and covariance. It's considered more reliable than IS because it accounts for the quality of generated images and provides better correlation with human judgment, making it the preferred metric for many GAN evaluations.