

## ASSIGNMENT-1:-

Summary of "Generative Adversarial Nets" (NIPS 2014)  
This paper introduces Generative Adversarial Networks (GANs), a novel framework for estimating generative models using an adversarial process. It proposes training two neural networks simultaneously:-

- 1) Generator (G):- Generates synthetic data that aims to resemble real data.
- 2) Discriminator (D):- Evaluates whether a given data sample is real (from the dataset) or fake (from the generator).

### Key Concepts:-

- \* The training process is modeled as a minimax game: The generator tries to complete realistic data to fool the discriminator, while the discriminator tries to distinguish between real and fake samples.
- \* The competition between two networks improves their performance until the generated samples become indistinguishable real data.
- \* Unlike previous generative models, GANs do not require Markov chains or approximate inference methods.

### Theoretical insights:-

- \* The paper proves that, in the ideal case where both  $G$  and  $D$  have infinite capacity and training time, the generator will converge to the true data distribution.

\* The loss function is derived from a "Jensen-Shannon divergence" minimization between the real and generated distributions.

### Experiments:

\* The authors evaluate GANs on MNIST, Toronto Face database (TFD), and CIFAR 10 datasets.

\* They demonstrate that GANs generate high-quality samples that are competitive with existing generative models.

\* The paper acknowledges the challenge of evaluating generative models and estimates likelihood using Parzen window-based methods.

### Advantages and Challenges:

#### Advantages:-

\* No need for Markov chains.

\* Uses only backpropagation for optimization.

\* Can generate sharp, high-dimensional images.

#### Challenges:-

\* Training instability: The generator and discriminator must be carefully synchronized.

\* No explicit probability density estimation for generated data.

#### Future Directions:-

\* Conditional GANs (for generating data conditioned on specific inputs).

\* Semi-supervised learning applications.

\* Improving training stability and efficiency.



This foundational work laid the groundwork for numerous advancements in generative modelling, leading to applications in image synthesis, style transfer, and AI-generated media.