Research Paper Analysis: Generative Adversarial Networks

Context:

This was a landmark paper when it was released in machine learning. Most influential unsupervised learning paper that introduced dual model systems that fight against each other to prove the other one wrong.

Approach:

Basically, The discriminative model is likewise a multilayer perceptron, and the generative model creates samples by sending random noise through it. We call this type of network adversarial nets. In this instance, we can only use the extremely effective backpropagation and dropout methods to train both models, and only forward propagation to sample from the generative model.

- Two models - generative and discriminative
- Both the models are multilayer perceptrons
- Generator takes z (noice) as input
- Discriminator takes as input data sample x and determines if it comes from real data or Generator
- Generator tries to minimize log (1 - D(G(z))) while Discriminator tries to maximize the probability of correct classification.
- Alternate between k steps of Discriminator training and 1 step of Generator training to keep Discriminator close to its best solution.

- When a multilayer perceptron is used to define G, numerous critical points in parameter space are introduced. Despite their lack of theoretical assurances, the great performance of multilayer perceptrons in practice implies that they are an acceptable model to utilize.

In other words, D and G play the following two-player minimax game with value function $V(G, D)$:

$$\min_G \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]. \quad (1)$$

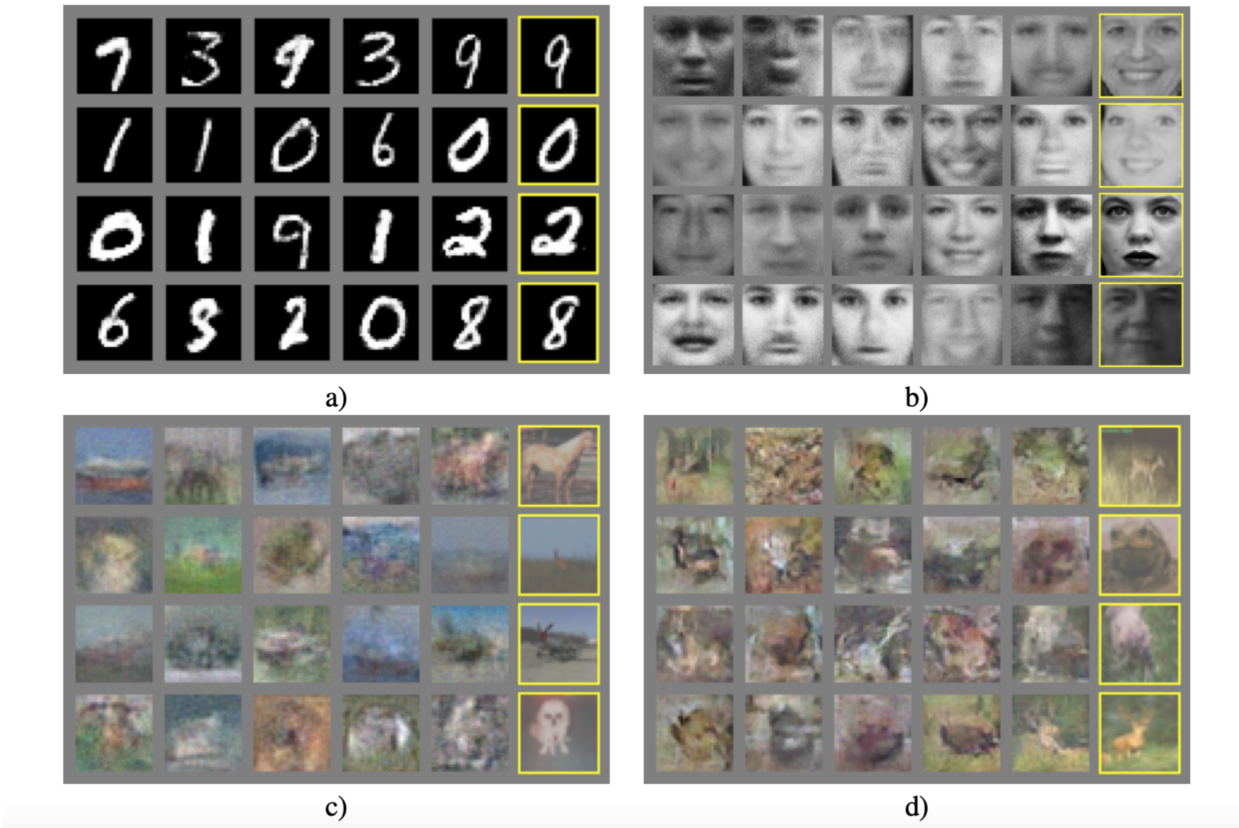
- The experimentation is performed on the MNIST dataset, Toronto Face database and CIFAR-10.
- The advantages of this method is that it does not require Markov chains for performing inference, a variety of functions and artforms can be used in this model, representing sharp distributions and fewer chances of copy from original data.

Limitations:

- Generator and Discriminator must be in perfect harmony.
- Generators may learn to sample data points that are indistinguishable from genuine data, but there is no explicit representation.

Experimentations:

- The experimentation is performed on the MNIST dataset, Toronto Face database and CIFAR-10
- In the experimentation, in MNIST dataset, GAN outperformed everyone else



Conclusion:

- This short paper was a demonstration of algorithm and model to utilize for various conditions and usage and as per the author The feasibility of the adversarial modeling framework has been provided in this paper, indicating that these research areas may be valuable.