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Research Article

Mathematical analysis of loss function of GAN and its loss function variants

Rayeesa Mehmood, Rumaan Bashir* and Kaiser J. Giri
Department of Computer Science, Islamic University of Science and Technology, Kashmir, Jammu and Kashmir, 192122, India

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Abstract
Generative adversarial networks (GANs) have turned up as the most widely used approaches for creating realistic samples. They're the effective latent variable models for learning complex real distributions. However, despite their enormous success and popularity, the process of training GANs remains challenging and suffers from a number of failures. These failures include mode collapse where the generator generates the same set of output for different inputs which finally leads to loss of diversity; non-convergence because of the diverging and oscillatory behaviors of both generator and discriminator while being trained; and vanishing or exploding gradients due to which either no learning or extremely slow learning takes place. In the past years, a variety of strategies for stabilizing GAN training have been explored which includes modified architectures, loss functions, and other methods. The choice of loss function has been found to be the most crucial part of the GAN model because it influences the vanishing gradient and model collapse directly. Viewing these loss functions as divergence minimization has provided a rich avenue of development. All of these factors make GAN training inherently unstable, and this instability is difficult to comprehend mathematically. This paper intends to provide a thorough mathematical explanation of these divergence minimization functions. It illustrates in great detail the two variants of the loss functions of the original GAN, their optimization to Kullback-Leibler (KL) divergence and Jensen-Shannon (JS) divergence along with their shortcomings. It also describes the loss functions of the different loss function GAN variants that have been proposed to mitigate these shortcomings as well as their minimization. The original GAN and its loss function variants have also been implemented using the standard MNIST, Fashion-MNIST, and CIFAR-10 datasets.

Keywords
Generative adversarial networks, Divergence minimization, Loss functions, Stable training, Mode collapse, Non-convergence.

1.Introduction
Machine learning has enjoyed a diversified history, having its origin in many interdisciplinary subjects like computational learning theory and pattern recognition, cognitive science, neuroscience, and other disciplines [1]. This field of computer science does not require machines to be programmed using static or rigid instructions in order to act. It focuses on developing algorithms that learn from the data and then make predictions based on that data set without human intervention. There are two important contemporary paradigms in machine learning. The first is generative or Bayesian learning and the other one is discriminative learning of classifiers [2, 3].

The generative model is a strong unsupervised learning method for learning any distribution of data and has experienced considerable success in a short amount of time. The idea behind such models is to generate new data instances or configurations. They can generate new photos of different types of objects that look like real ones. They enable users to provide information about the problem to the learning algorithm using prior distributions, structured models, independence graphs, probabilistic reasoning, Markov assumptions, and latent variables. It includes the data's distribution and indicates the likelihood of a certain example. For instance, the models used to determine the subsequent word in a series belong to the category of generative models because each word in the sequence is assigned a probability. These generative models include mixtures of multinomial, mixtures of experts, naïve

*Author for correspondence