Generative Adversarial Networks (GAN) Review

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Abstract: **Latest research in Deep Learning Networks (DLN), the frontier of machine versus human, is making fast strides into harder problems of learning and cognition. Generative Adversarial networks (GAN) are the state of the art learning networks showing promise in this direction. GANs are actively researched and pursued both in academics as well as business enterprises. An understanding of this new machine learning technique (GANs) and their possible usages are discussed in this paper. Results from a representative problem of one dimensional data are presented.**

Index Terms: **Generative Adversarial Networks (GAN), Convolution networks (CNN), Multilayer perceptron (MLP), Generator, Discriminator, Log likely hood function, statistical distributions and sampling of distributions.**

I. Introduction

With advent and success of artificial neural networks, artificial intelligence (AI) landscape has regained momentum in solving real world problems. Figure 1 shows the landscape of AI in relation to learning networks. Deep Learning is at the center of this momentum.

Human brain being massively parallel in structure and also hierarchical is probably capable of continuous activation both with current as well as future perceptions. Neuronal activations in human brain are influenced by incoming sensory information as well as top-down projections. Top down projections, probably, indicate expectation about future incoming information, which is typical of generative modeling[1]. However, this is different from bottom-up learning models, also called as feed forward learning deep neural networks (DNN). These feedforward learning machines are greatly successful in classification problems which have become important tools in decision making. However, it is difficult to figure out the source of classification errors in these feedforward networks which rely on sensory-input->learn->classify paradigm. Top-down learning, on the other hand, has the potential of explaining the information from sensory inputs by subtracting its predictions from sensor input. However, human brain is not confined to either of the approaches, but presumably a combination of both. From the motivation of the top-down approach of human brain, latest research is focused on Generative Adversarial networks (GAN) which fall in the area of deep learning. Following sections review some of the latest research publications on GAN and bring out an understanding of underlying learning algorithm through one dimensional data. Many of the research publications are still under review.

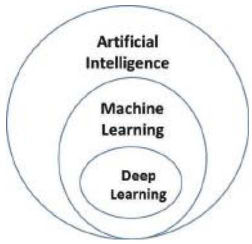

Figure.1 AI landscape

II. Generative Adversarial Networks (GAN)

Learning machines can broadly be categorized as discriminative and generative. While the goal of the former is to be able to classify information (objects in a limited definition) as precisely as possible, the later focusses on understanding the underlying distribution in the input information. Generative modeling attempts to mimic a known input. As an example, it is possible to create a mimicked version of handwritten symbols from the knowledge of a given symbol set or to create new images given a set of images. It would be difficult to distinguish between original and mimicked version of these objects. These Generative models are a kind of unsupervised learning machines. Unsupervised learning initially started with Kohonen feature maps, also called Self Organizing Maps(SOM) and progressed to recent Autoencoders (AE) which have become popular in Deep Learning (many publications on both SOM and AE are available in WEB). Unsupervised learning discovers the structure of the input space. Both deterministic networks based on back propagation (BPN) and probabilistic networks like Restricted Boltzman Machines (RBMS) are examples of unsupervised learning machines. However, these are still limited in the sense they are not completely generative models. Generative Adversarial networks (GAN) are introduced by Ian Goodfellow[2] and are currently being actively researched. Figure 2 describes a general architecture of GAN.

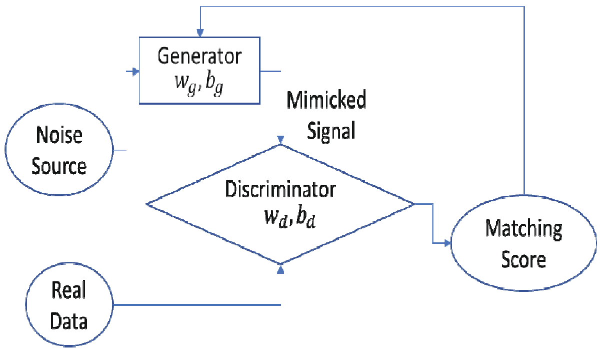

Figure.2 General of a GAN

GAN has two networks, Generative and discriminative, which are simultaneously trained. Generative network tries to discover the underlying distribution in real data without really having seen this data and Discriminative network attempts to estimate the probability that its input is real data and not from Generator. Both the networks can be of any type i.e. multilayer perceptron (MLP), Restricted Boltzmann Machine (RBM), Convolution Neural Network (CNN) etc. Generator objective is to mimic the underlying distribution in real data without really having access to this data. Discriminator tries to distinguish between real and mimicked data. Unlike in single network configuration, learning happens in two networks simultaneously with different objective functions. Training results in arriving at network parameters like (w_g, b_g) and (w_d, b_d) for generator and discriminator. While Generator's objective is to maximize its capability to mimic real data, the discriminator tries to maximize its ability to distinguish between data produced by generator versus real data. Equations 1 to 3 summarize this twin objective in terms of loss functions of Generator network, Discriminator Network and overall Adversarial Network.

Loss Function of Generator : $L_g = -\log(D(z))$ (1)
Loss Function of Discriminator : $L_d = -\log(D(i))$ (2)
Overall Loss Function = $L_g + L_d$ (3)

A tutorial on GAN is presented by Goodfelow[3] and Lili[22]. Following sections review the current literature followed by understanding of GAN using a one-dimensional simulated data implemented in Tensorflow.

III LITERATURE SURVEY OF GAN

Research publications on GAN have started in 2016 and gained momentum in 2017. Alec Redford[4] proposed convolution nets, as used in deep learning, both for the generator as well as the discriminator and applied for image representations. The claim in this paper is centered on using CNNs which are used in supervised learning, for unsupervised learning tasks. Model instability while training for longer epochs is observed. Paulin[5] used GAN based approach for semantic segmentation of images. This paper proposes for the first time a hybrid loss term consisting of (a) multi-class cross-entropy term and (b) adversarial CNN output. Loss term is a function of two parameters belonging to segmentation and adversarial models. Results on PASCAL VOC 2121 data sets indicate improved semantic segmentation accuracy using adversarial model. Arna Ghosh[6] applied GAN for handwriting profile in which deep convolution GAN (DCGAN) are used. The results of experiments are yet to be published. However, work in this area can become useful for detecting forged documents and signatures. The work related is in initial stages. Han Zhang[7] used stacked GANs to generate images from text descriptions. The task of creating photo realistic images from text is divided into two stages (1) sketching the primitive shape with basic color attributes with background generated from noise generator (2) correcting the low resolution image in text description and improving the background. Separate GAN is used for the two stages. Loss functions are similar to what is proposed[2]. Claim is on improved text to photo realistic image generation to other methods like variational auto encoders. Xun Huang[8] uses stacked GAN with pretrained discriminator and hierarchical arranged GANs. Each of the GANs has a loss function consisting of adversarial, conditional and entropy loss terms. Entropy loss term is a contribution in this publication. An interesting application of preserving original identity in an image after aging of person, is studied by Grigory Antipov[9]; this is in contrast to the approach of generating characteristics of a given image of a person. First a GAN is trained to generate good quality images with age characteristics while an optimization is used to improve the image while preserving the aging. Yet another application in the field of entertainment and art, cartoon image is presented by Yifan Liu[10]. In this GANs are used for auto painting (colorization) a given sketch. Pixel-to-pixel model constraints are added to loss function of GAN to better coloring. Marco Marchesi [11] investigated DCNNGAN for generating high quality mega pixel images. Limited data is used as opposed to thousands of images used by the other researchers. Interestingly, an application of GANs for cosmological data is reported by Mustafa Mustafa[12] and the area is gravitational lensing to sense dark energy in galaxies. Standard normal distribution of 64 dimension is used for generator. Network architecture follows DCGAN. Zhigang Li[13] addressed the problem of preserving identity in human faces using GAN with a generator to create faces and FaceNet as discriminator. This is a typical application of generating different facial orientations of a criminal with available frontal view (only front view); Hamid Eghbal-zaseh[14] introduced a general likelihood estimation for assessing the quality of generated images using GAN. The advantage of this method is that it is independent of GAN architecture as well as method of training. Jerry Li[15] brought out the theoretical basis of GAN and explained the collapse of discriminator with a proof. The difference between optimality of discriminator dynamics and first order dynamical systems is compared. Michael O.Vertolli[16] introduced a method of training and evaluation of GAN generated images. Auto Encoders are used in AE-GAN. It is shown that different distance metrics in loss function capture different parameters in images. Chan Shing[17] applied GAN to generate Geological data in sub-surface fields. It is concluded that the flow physics generated by

GAN closely resembles the reference data. Also, PCA performance was observed to be not accurate. Chao Shang[18] has handled one of the important topics in data science i.e. imputing the missing data using GANs. Imputation of missing data of health care dataset as well as MISNST are demonstrated using CycleGAN. It was reported that imputing multimodal data in large data sets was not possible. Compressed sensing MRI, a recent technique to reduce time of acquisition of MRI images, is presented by Tran Minh Quan[19]. Loss function contains not only the regular GAN term but terms containing frequency and amplitude terms. Daniel Mischesanti[20] studied GANs for speech denoising and enhancement and it is compared with classical approach based on STSE-MMSE algorithm and reported better SNR. The above research effort is diverse and indicates that loss function originally formulated by Ian Goodfellow[2], needs modification to suit training and domain requirements. Jaime Deverall[21] presented an interesting application of designing shoes using conditional GAN. The difficulties in training CGAN is attributed to dataset; many ambiguous comparisons are reported. By the time of writing this article more than 100 publications are added in just one year. GAN being very nascent, this paper focusses on bringing an understanding of their architecture and training using a one-dimensional data and single layer perceptron networks both for generator and discriminator networks.

IV Architecture of GANs

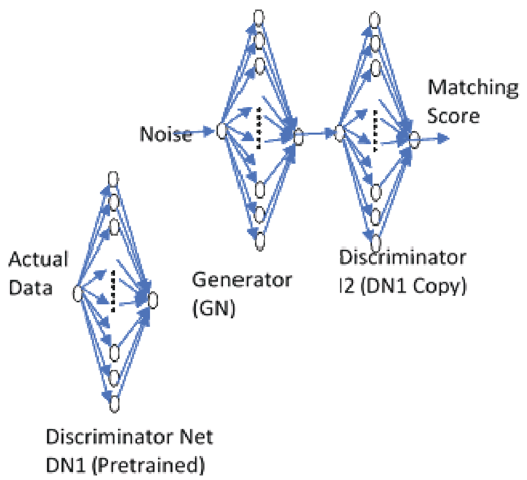

Figure.3 1-D Single layer perceprtron GAN

Figure 2 shows typical building blocks of a simple GAN using single layer perceptron networks for both generator as well as discriminator. Major components of GAN are (a) Generator (GN) and Discriminator (DN) networks (b) noise generator and (c) Optimizer. GN and DN simultaneously perform the tasks of mimicking and recognizing. The learning parameters in this simple network are weights, biases of both the generator as well as discriminator. However, both the generator as well as discriminator networks can be any networks like RBMs and CNNs. The learning function for input to hidden layer is selected as ReLu, but can be anything whereas, the function from hidden layer to output is chosen as sigmoid for discriminator network. Noise source is selected as random sample of random distribution and real data is a randomly sampled Gaussian distribution. Gradient descent algorithm is chosen as optimizer.

Initially discriminator is trained with actual data and part of artificial data. During this phase of training back propagation is applied to discriminator only and generator just generates data based on random sampling of noise source. The learning parameters of discriminator are frozen in this phase. In the second phase, complete adversarial network is trained with generator trying to improve its output based on error reported by discriminator. For demonstration of GAN, an open source code, suitably modified, is used and actual data and corresponding noise are shown in figures 3 and 4.

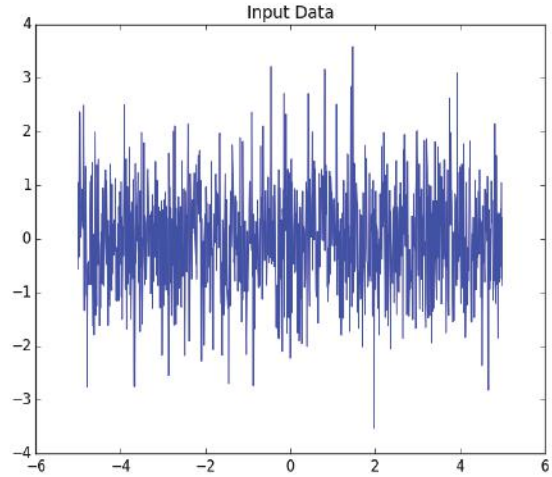

Figure.4 Actual Input to discriminator

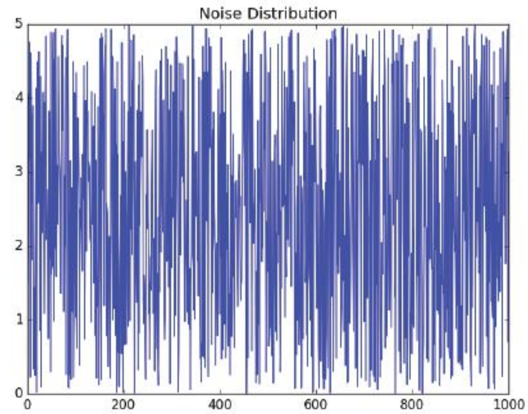

Figure.5 Noise data input to Generator

Figures 6 to 10 describe different outputs of GAN using simulation code. Each figure shows decision boundary of discriminator, real data and generator created mimicked data for different combinations of learning functions of GN and DN. Figures also show performance of GAN with different number of neurons in the hidden layers. Results are produced with 1000 iterations to understand the performance of GAN. It can be seen that for the chosen network, the learning function combination with changing number of hidden layer neurons, the decision boundary (green line) changes. Some combinations of learning functions fail to discriminate the data. Desired decision boundary is to have probability of 0.5 i.e. the DN should not be able to clearly discriminate between real input and mimicked input.

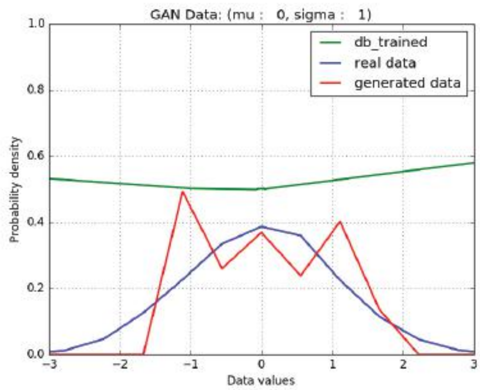

Figure.6 GAN outputs with sigmoid learning function (GN&DN) 32 neurons in hidden layer

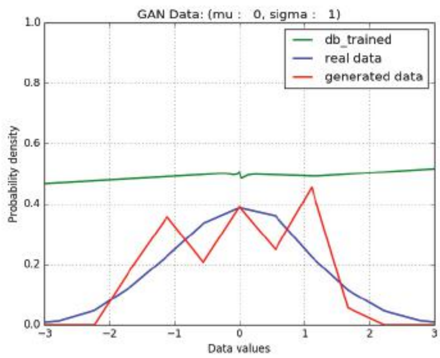

Figure.7 GAN outputs with sigmoid learning function (GN&DN) 256 neurons in hidden layer

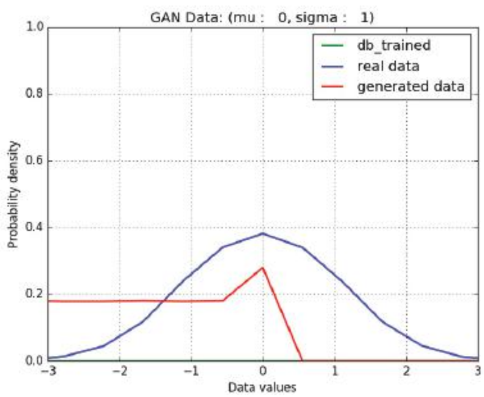

Figure.8 GAN outputs with ReLu learning function (GN&DN) 32 neurons in hidden layer

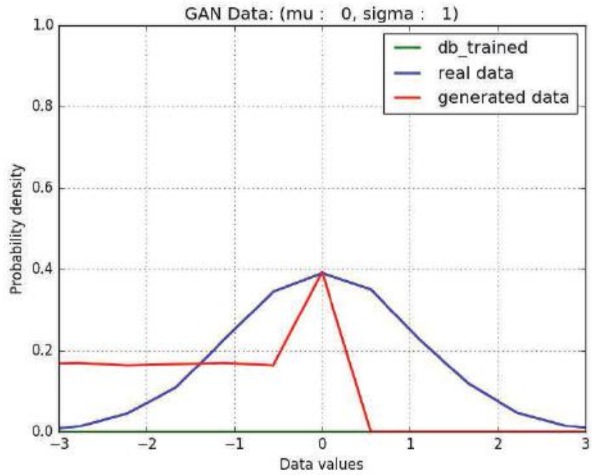

Figure.9 GAN outputs with ReLu learning function (GN&DN) 256 neurons in hidden layer

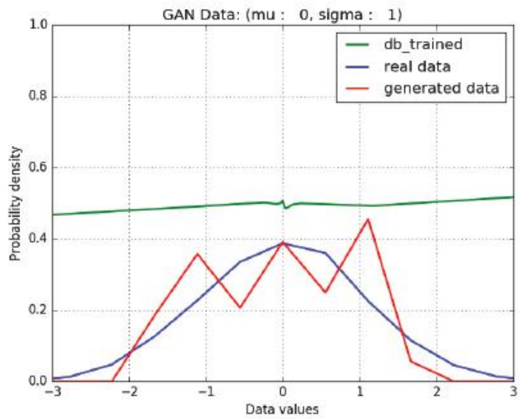

Figure.10 GAN outputs with mixed Sigmoid and ReLu learning functions and 32 neurons in hidden layer

V. CONCLUSIONS

GANs are the most recent machine learning algorithm and they are based on two player game theory. The research in this area started very recently [2016-17] and application areas include medical imaging, art, forensic sciences, industrial processes and power plant real time simulation etc. It is seen that considerable effort is required to arrive at an optimum architecture of Generator and Discriminator networks. And the selection of an optimizer for training is a serious issue. There is scope of introducing different loss functions for different applications. It is expected that good amount of research reporting will come up by 2018. The success of GAN as a possible disruptive technique largely depends on (a) simple and robust optimizer (b) easy rules to decide overall GAN architecture for different applications. The authors conclude that GANs offer a good scope for both academic and industry application development in the immediate future.

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