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Hypothetical Exploration on Generative Adversarial Networks

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***Abstract*—To train any Neural Networks and to design a classifier we need huge datasets in the same domain. Normally 60% of datasets used for training Neural Networks and 40% of datasets for testing the Neural Networks. But in the real world we cannot get the dataset for all applications physically. So, a new concept Generative Adversarial Networks proposed by Ian Goodfellow et al. in 2014 [1] to create similar set of datasets to train and test the Neural networks, which is breakthrough in the field of Neural Networks to design the classifiers. The Generative Adversarial Networks (GANs) are a class of artificial intelligence algorithms used in unsupervised machine learning, implemented by a system of two neural networks contesting with each other in a Zero-Sum Game framework. GANs has huge potential as they can learn to mimic any distribution of data. That is, GANs can be taught to create worlds eerily similar to our own in any domain: images, music, speech, prose. The GANs learnt representations may be used in a variety of applications, including semantic image editing, style transfer, image synthesis, image super-resolution and classification.**

***Index Terms*—Probabilistic Computation, Neural Networks, Convolutional Neural Networks, Generative Adversarial Networks, Laplacian Pyramid of Adversarial Networks.**

I. Introduction

GENERATIVE Adversarial Networks are emanated as trending technology in field of Machine Learning. The GANs are deep neural networks technique for semi-supervised and unsupervised learning. The GANs are proposed by Ian Goodfellow in 2014 [1]. The GANs are framework for estimating generative models via an adversarial process, i.e., we have two neural networks one is Generator which generates the data such as images, speech, video, etc., and other one is Discriminator which evaluates the generated data with respect to original data and try to differ the fake data from real data. In this process for each epoch the results get better and better. But here the Generator has no access to original/real data, the only way it learns is through the interaction with Discriminator. The Discriminator has access to both real and generated data. The Generator is trained with respect to feedback from the Discriminator.

The entire setup can be interpreted as a Zero-Sum Game Framework(ZSGF), which follows a min-max character. On the one hand, Discriminator tries to maximize the probability of correctly distinguishing between real and fake data by changing its decision boundary. On the other hand, Generator tries to minimize the probability of its generated samples being classified as fake. The outcome is fed back to both networks using back-propagation. It allows both networks to iteratively improve their policy on how to decide and act within their respective tasks.

The Generator and Discriminator networks are typically implemented by multi-layer networks which consists of convolution or full-connected layers. The Generator and Discriminator networks are two type of different neural networks. Consider the generator network as mapping from some representation space, called a latent space, to the space of the data, then we may express this as $G : G(y) \rightarrow R^{|x|}$ where $y \in R^{|x|}$ is a sample from the latent space, $x \in R^{|x|}$ is an image and $|.|$ denotes the number of dimensions.

The discriminator network(D), is characterized as a function that maps image data to a probability that the image is from the real data distribution, $D : D(x) \rightarrow (0, 1)$. For a fixed generator(G), the discriminator(D) fig(1), will be trained to classify images as the training data (real, close to 1) or from a generator (fake, close to 0). When the discriminator is optimal, it may be frozen, and the generator(G), may continue to be trained so as to lower the accuracy of the discriminator. If the generator data is able to match the real data distribution perfectly then the discriminator will be confused, predicting 0.5 for all inputs. In practice, the discriminator might not be trained until it is optimal.

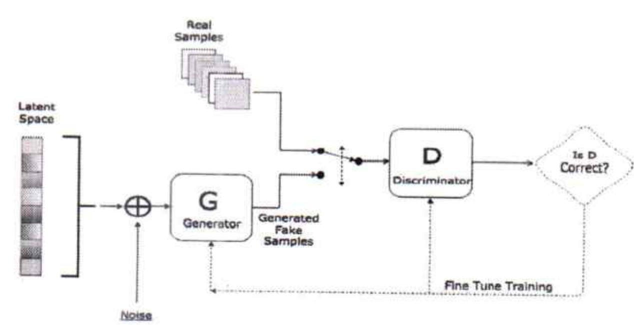

Fig. 1: Generative Adversarial Networks

II. Related Work

One can view the principles of generative models by creating comparisons with standard techniques in signal process and knowledge analysis. As an example, signal process makes wide use of the concept of representing a signal as the weighted combination of basic functions. Basis

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functions underlying standard techniques such as Fourier-based and wavelet representations. Data-driven approaches to constructing basis functions can be traced back to the Hotelling [2] transform, rooted in Pearson's observation that principal components minimize a reconstruction error according to a minimum squared error criterion. Despite its wide use, standard Principal Component Analysis (PCA) doesn't have associate visible applied mathematics model for the ascertained knowledge, though it's been shown that the bases of PCA is also derived as a most probability parameter estimation drawback.

Despite wide adoption, PCA itself is restricted – the idea functions emerge because the eigenvectors of the covariance matrix over observations of the input file, and also the mapping from the illustration area back to signal or image area is linear. So, we've got each a shallow and a linear mapping, limiting the complexity of the model, and thus of the information, that may be represented.

Independent Component Analysis (ICA) provides another level up in sophistication, during which the signal components no longer need to be orthogonal; mixing coefficients used to blend components together to construct samples of data are merely considered to be statistically independent ICA has varied formulations that dissent in their objective functions used throughout estimating signal components, or within the generative model that expresses how signals or pictures are generated from those components. A recent innovation explored through ICA is Noise Contrastive Estimation (NCE), this could be seen as approaching the spirit of GANs [3], the objective function for learning independent components compares a statistic applied to noise with that produced by a candidate generative model [4]. The original NCE approach did not include updates to the generator.

$$L = E[logP(S = real|Xreal)] + E[logP(S = fake|Xfake)] \quad (1)$$

III. GAN Architectures:

A. Fully Connected GANs

The Fully Connected GANs is first neural network which used fully connected neural networks for both Generator and Discriminator. It is simple type of GAN architecture. GANs utilizes two neural networks trained in opposition to one another. These were proposed by Ian Goodfellow et al. in their research paper "Generative Adversarial Networks" in 2008 [1]. In the first network which is a generator G, it takes a random noise as an input and outputs a fake image Xfake = G(z). While the discriminator takes a random sample of training sample of an image that is generated by the generator and outputs a probabilistic distribution P(S—X) = D(X) over a set of possible image sources. Both Discriminator(D) and Generator(G) are trained simultaneously and the hyperparameters are adjusted based on optimizing the loss and varying the randomness. With the error and losses that are generated by the discriminator, the randomness in the generator is updated so that generated images are realistic. Mathematically the log likelihood or the rectified randomness that is updated with respect to the discriminator is given by

$$L = E[logP(S = real|Xreal)] + E[logP(S = fake|Xfake)] \quad (2)$$

One of the main most common problems that are widely addressed by Generative Adversarial Networks is when there is a huge dataset the leverage additional modularity's for better predictions. Few examples include vector representation for labels in which geometrical relations are semantically meaningful here the prediction errors which are generated by the neural network are generalized to labels by using simple linear mapping from image label space to word representation latency for improving the classification performance [5].

The Fully Connected GANs are mainly applied to relatively simple image datasets, namely MNIST (hand written digits), CIFAR-10 [6] (natural images) and the Toronto Face Dataset (TFD).

B. Convolutional GANs

In recent years, supervised learning with convolutional networks (CNNs) has seen huge adoption in various applications. Comparatively the less attention was given to unsupervised learning with CNNs. Early experiments on Fully Connected GANs suggested that it is more difficult to train generator and discriminator using CNNs with same level as the one used for supervised learning. In this work, to bridge the gap between the success of CNNs for supervised learning and unsupervised learning.

A class of CNNs called Deep Convolutional Generative Adversarial Networks (DCGANs) [7] fig(2) are demonstrated as that they are a strong candidate for unsupervised learning. DCGANs are a set of constraints on the architectural topology of Convolutional GANs that make them stable to train in most settings. Training on various image datasets, it has shown convincing evidence that deep convolutional adversarial pair learns a hierarchy of representations from object parts to scenes in both the generator and discriminator. Additionally, it uses the learned features for novel tasks - demonstrating their applicability as general image representations.

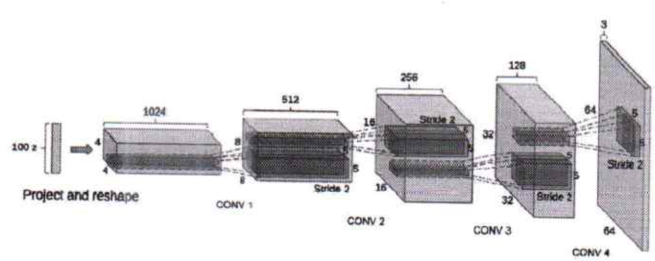

Fig. 2: DCGAN generator used for LSUN scene modeling

Deep learning approaches have proven significantly effective at discriminative tasks, such as object classification [8]. However, generative tasks havent obtained the same level of success, despite numerous efforts [9]. Against this background, the Laplacian Pyramid of Adversarial Networks (LAP-GAN) [10] introduces a generative parametric model capable of producing high quality samples. This approach uses a cascade of convolutional networks within a Laplacian pyramid framework to generate images in a coarse-to-fine fashion. At each level of the pyramid, a separate generative convnet model is trained using the GANs approach [1]. Samples drawn from the model are of significantly higher quality than alternate approaches.

By using volumetric Convolutions, Wu et al. [11] presented GANs that are able to synthesize 3D data samples. This method maps the 2D images to 3D version of objects. This approach combines the merits of both general-adversarial modeling [Goodfellow et al., 2014 [1], Radford et al., 2016 [7]] and volumetric convolutional networks [Maturana and Scherer, 2015 [12]]. Different from traditional heuristic criteria, generative-adversarial modeling introduces an adversarial discriminator to classify whether an object is synthesized or real.

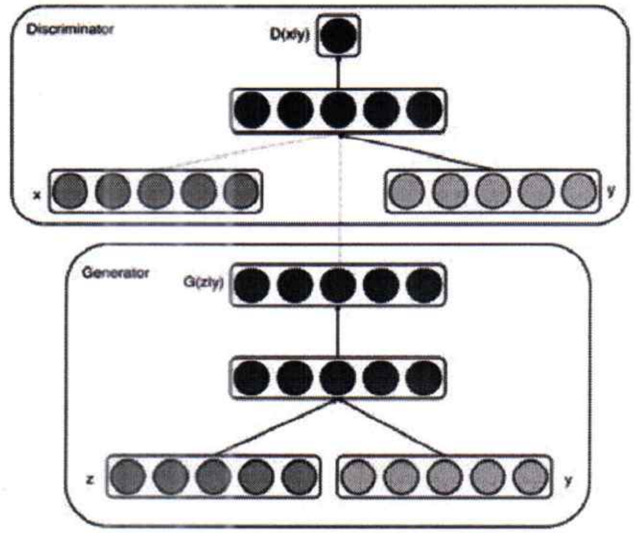

Fig. 3: Conditional GANs

C. Conditional GANs

The M. Mirza et al. [13] introduced the conditional version of GANs, which can be constructed by simply feeding the data to condition on to both the generator and discriminator. Conditional GANs have the advantage of being able to provide better representations for multi-modal data generation. GANs when extended with some extra information mostly of auxiliary information (class labels or data of other modularities). This information is fed into the network by adding an additional layer. Once the new layer is added to both the generator and discriminatory network, we can perform conditioning by feeding in this labelled data. The noise is usually a hidden representation or a layer in the generator network and the adversarial training framework allows for considerable composition [14]. If we consider a discriminator with x as an input x and y as a discriminative function which defines the fakeness or realness of image in a multilayer perceptron then mathematically the objective is calculated as

$$
\begin{aligned}
min_G max_D V(D,G) = E_{\infty \sim Pdata(x)}[log D(\frac{x}{y})] \quad (3) \\
+ E_{\infty \sim P_z(z)}[log(1 - D(G(\frac{z}{y})))]
\end{aligned}
$$

and the pictorial representation is shown in fig(3)

A common approach to semi-supervised learning is to combine a supervised and unsupervised objective during training. As a result, unlabeled data can be leveraged to aid the supervised task.

D. Inference Model GANs

GANs lacks a way to map a given observation to a vector in latent space. Antonia Creswell et al. [15] introduces techniques for projecting image samples into the latent space using any pre-trained GAN. The Dumoulin et al. proposed Adversarially learned inference (ALI) [16] model, which jointly learns a generation network and an inference network using an adversarial process. The inference network maps training examples in data space to the space of latent variables and the generation network maps samples from stochastic latent variables to the data space. A discriminative network is trained to distinguish between joint latent/data-space samples from the generative network and joint samples from the inference network.

The Donahue introduces Bidirectional GANs [17] as a means of learning this inverse mapping, and demonstrate that the resulting learned feature representation is useful for auxiliary supervised discrimination tasks, competitive with contemporary approaches to unsupervised and self-supervised feature learning. The fidelity of reconstructed data samples synthesized using an ALIBiGAN are poor. The fidelity of samples may be improved with an additional adversarial cost on the distribution of data samples and their reconstructions [18].

E. Adversarial AutoEncoders (AAE)

The network composed of an "encoder" and "decoder" are Autoencoders, that learn to map data to an internal latent representation and out again. That is, they learn a deterministic mapping from a data space into a latent or representation space, and a mapping from the latent space back to data space. The composition of these two mappings results in a "reconstruction", and the two mappings are trained such that a reconstructed image is as close as possible to the original.

Autoencoders are reminiscent of the perfect reconstruction filter banks that are widely used in image and signal processing. Autoencoders generally learn non-linear mappings in both directions. Further, when implemented with deep networks, the possible architectures that can be used to implement autoencoders are remarkably flexible. Training is unsupervised as backpropagation being applied between the reconstructed image and the original in order to learn the parameters of both the encoder and the decoder fig(4).

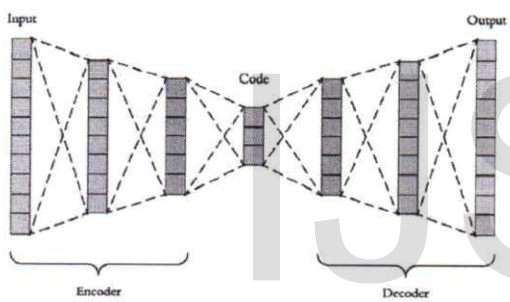

Fig. 4: Adversarial AutoEncoders (AAE)

There is a need that the latent space to have a useful organization. Additionally, one may want to perform feedforward, ancestral sampling [19] from an autoencoder. Adversarial training provides a route to achieve above two goals. Specifically, adversarial training is applied between the latent space and a desired prior distribution on the latent space. This results in a combined loss function [20] that reflects both the reconstruction error and a measure of how different the distribution of the prior is from that produced by a candidate encoding network. This approach is akin to a variational autoencoder (VAE) [21] for which the latent space GAN plays the role of the KL-divergence term of the loss function.

Mescheder et al. [22] adversarial training unified variational autoencoders in the form of the Adversarial Variational Bayes (AVB) framework. Similar ideas were presented in Ian Goodfellow's NIPS 2016 tutorial [23]. AVB tries to optimise the criterion as that of variational autoencoders, but uses an adversarial training objective rather than the Kullback-Leibler divergence.

F. InfoGAN

Xi Chen et. al [24] describes InfoGAN, an information-theoretic extension to the Generative Adversarial Network that is able to learn disentangled representations in a completely unsupervised manner. InfoGAN maximizes the mutual information between a small subset of the latent variables and the observation. Specifically, InfoGAN successfully disentangles writing styles from digit shapes on the MNIST dataset, pose from lighting of 3D rendered images, and background digits from the central digit on the Street View House Numbers (SVHN) dataset. InfoGAN discovers visual concepts that include hair styles, presence/absence of eyeglasses, and emotions on the CelebA face dataset. InfoGAN learns interpretable representations by existing supervised methods.

IV. Application of GANs

There are numerous applications for GANs, which made impossible things possible in real world. GANs are next biggest invention in the field of science and technology. Many problems can be solved by using GANs. Here are few notable applications of GANs.

A. Classification and Regression

The neural network can be reused for other tasks. For example, outputs of the convolutional layers of the discriminator can be used as a feature extractor, with simple linear models fitted on top of these features using a modest quantity of (image; label) pairs [7]. The quality of the unsupervised representations within a DCGAN network have been assessed by applying a regularized L2- SVM classifier to a feature vector extracted from the (trained) discriminator [7]. Even those that were disjoint from the original training data, good classification scores were achieved using this approach on both supervised and semi-supervised datasets.

The quality of the data representation may be improved when adversarial training includes jointly learning an inference mechanism such as with an ALI [16]. A representation vector was built using last three hidden layers of the ALI encoder, a similar L2-SVM classifier, achieved a misclassification rate significantly lower than the DCGAN [16]. Additionally, ALI has achieved state of-the art classification results when label information is incorporated into the training routine.

When labelled training data is in limited supply, adversarial training may also be used to synthesize more training samples. Shrivastava et al. [25] use GANs to refine synthetic images, while maintaining their annotation information. Shrivastava et al. [25] achieved state-of-the-art performance on pose and gaze estimation tasks by training models only on GAN-refined synthetic images (i.e. no real training data). Similarly, good results were obtained for gaze estimation and prediction using a spatiotemporal GAN architecture [26]. In some cases, models do not generalize well when trained on synthetic data and applied to real data [27]. To address this problem Bousmalis et al. [27] proposes adapting synthetic samples from a source domain to match a target domain using adversarial training. Additionally, using multiple GANs – one per domain – with tied weights to synthesize pairs of corresponding images samples from different domains which is proposed by Liu et al. [28].

Even as new and diverse applications in computer vision are explored, classification tasks are likely to remain an important quantitative tool for performance assessment of GANs.

B. Image Synthesis

Recent research on the GAN focuses on improving the quality and utility of the image generation capabilities. The LAPGAN model introduced a cascade of convolutional networks within a Laplacian pyramid framework to generate images in a coarse-to-fine fashion [10]. A similar approach is employed by Huang et al. [29] with GANs operating on intermediate representations rather than lower resolution images.

LAPGAN also extended the conditional version of the GAN model where both G and D networks receive additional label information as input; this technique has proved useful and is now a common practice to improve image quality. This idea of GAN learning was later extended to include natural language. For example, Reed et al. [30] describe about reverse captioning which is a GAN architecture to synthesize images from text descriptions. For example, there is a text caption of an animal such as "White big bulit and with four legs and hump on back and two horns", the trained GAN can generate several possible images that match the description.

In addition to learning on text descriptions, the Generative Adversarial What-Where Network (GAWWN) conditions on image location [31]. The large images could be built up incrementally with textual descriptions of parts and user-supplied bounding boxes using GAWWN system supported interactive interface.

Conditional GANs allow us to develop tools for intuitively editing images – for example editing the colour and hair style of a person in an image, making them wear hats and glasses or making them look younger or older [32].

C. Image-to-image translation

Conditional adversarial networks are well suited for translating an input image into an output image, which is a recurring theme in computer graphics, image processing, and computer vision. The pix2pix model gives a general-purpose solution to this family of problems [14]. The pix2pix model not only learning the mapping from input image to output image, but also constructs a loss function to train this mapping. The pix2pix model has demonstrated effective results for different problems of computer vision which had previously required separate machinery, including semantic segmentation, generating maps from aerial photos, and colorization of black and white images. The idea of using GANs to first synthesize surface-normal maps (similar to depth maps) and then map these images to natural scenes is presented by Wang et al [33].

This work is extended by introducing CycleGAN a cycle consistency loss that attempts to preserve the original image after a cycle of translation and reverse translation. In this matching pairs of images are no longer needed for training. This makes data preparation simple, and opens the technique to a larger family of applications. For example, artistic style transfer [34] renders natural images in the style of artists by simply being trained on an unpaired collection of paintings and natural images.

D. Super Resolution GAN

A high-resolution image is generated from a lower resolution image, with the trained model inferring photo-realistic details while up-sampling this is known as Super-resolution. The Super Resolution GAN(SRGAN) model [35] extends earlier efforts by adding an adversarial loss component which constrains images to reside on the manifold of natural images.

The SRGAN generator is conditioned on a low-resolution image, and infers photo-realistic natural images with 4x up-scaling factors. The adversarial loss is one component of a larger loss function, which also includes perceptual loss from a pretrained classifier, and a regularization loss that encourages spatially coherent images. Here, the adversarial loss constrains the overall solution to the manifold of natural images, producing perceptually more convincing solutions.

Customizing deep learning applications is not often possible as there is less availability of relevant curated training datasets. However, SRGAN is straightforward to customize to specific domains, as new training image pairs can easily be constructed by down-sampling a corpus of high-resolution images. This is an important consideration in practice, since the inferred photo-realistic details that the GAN generates will vary depending on the domain of images used in the training set.

V. Conclusion

Since, the discovery of Computers, the Humans are able to solve any particular problem by formulating the Mathematical models and applying algorithms. In this era of Artificial Intelligence, Machine Learning is key field which has potential to solve any problem by making Machine learn and react on its own without being explicitly coded. Generative Adversarial Networks are emanated as trending technology in field of Machine Learning. The GANs are deep neural networks technique for semi-supervised and unsupervised learning. The GAN's are framework for estimating generative models via an adversarial process. Within the GANs there are many opportunities for developments in theory and algorithms, and with the power of deep networks, there are vast opportunities for new applications.

GANs produce the synthetic images generated from the given original image data sets with high accuracy and upscale the number of images and resolution by taking the classification features.

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