GANs: Initial Boost, Working and Classification Scheme for its Application

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ABSTRACT
Neural networks have helped make machine learning considerably more efficient. Seeing the use of various constructs of neural networks being quite direct, of course with necessary tuning, it can said that over a while they have also got a notion of templates. Generative Adversarial Networks (GANs) too, is considered as a template of neural networks. It involves the use of constant feedback and feedforward loops kind of arrangement of networks. This cycle progressively improves output. The emergence of GANs saw the unfolding of possibilities to solve many problems that one couldn't at all or even if one could solve them, the solutions were not feasible. Its potential is seen on a huge scale. It can also bring about impact in many creative areas like fashion, entertainment, etc. Because of the very construct of GANs, it helps make a lot of problems that were in the creative space, now doable. In this paper, the authors have discussed the initial points of influence that directly or even indirectly influenced the need and emergence of GANs, but before diving into that they have articulated a brief overview of the working of GANs and finally have put forth a classification scheme for the applications of GANs based on currently seen uses of it.

General Terms
Techniques, Applications, Neural Networks and Influence Points.

Keywords
Generative and Adversarial Networks (GANs), Neural Network, Machine Learning.

1. INTRODUCTION
Making the computer do creative tasks is difficult. To achieve the various applications where machine learning solutions fit, it was the same area where the solutions of these creativity related problems were expected to be solved. One hurdle before GANs was that computers couldn't feasibly and accurately combine 2 or more things that form a new thing which still abides the constraint followed by the domain of the input function. Hence one peculiar aspect of understanding why computers and machine learning, in particular, were not able to conquer was the accuracy of constraints & completely new output.

GANs also lead to an increase in the ability of a person in the sense that the discussed technology enables one to extend what they know and generate new outputs in the known area.

A popular IOS application called FaceApp is an appropriate case study in our context. Fundamentally, it is an Image Processing Based app. It can process user's images to transform the contents of it. To use the app, the user can click a selfie or use an already available picture from his/her phone gallery and give it to the aforementioned app for processing.

So, FaceApp rather than using Image Stacking or Pixel Manipulation uses Artificial Intelligence (AI) to bring changes in the facial features. It makes use of the GANs to create these very lifelike images. And this very quality of it makes it popular, exciting and technical trustable. [1]

Currently, there are few great and safe uses of GANs, but on the contrary, there are also some implementations which may become harmful in the near future, if the use of discussed technology is not regulated. Use of the technology by malevolent developers can lead to some serious harm to society e.g. Deepfake app.

Fake content is a very usual issue and has been present in the digital sphere. Particularly, after the introduction of photo-editing, image creation and graphic design software, it did increase considerably. Deepfake has been used so far to create such fake news, malicious hoaxes and adult videos. Deepfake is a GANs based product of deep learning. In this GANs create fake worlds that are very similar to real worlds. This software can be misused and can affect the prestige and reputation of a person or a group of individuals even if the contents fakeness can be distinguished by a personal eye in many cases. [2]

2. WORKING OF GANS
GAN is a specific type of neural network. It is a model for unsupervised machine learning. Unsupervised machine learning is used when you don’t have data. In this, the system is tested with different data and analysed to give results while in supervised learning the authors classify the data. E.g. whether the email is spam or not is a supervised machine learning problem.

Use of the same is to create worlds similar to our own, in any domain: images, music, speech, prose. They are artists who work like robots in a sense, and their output is quite great.

It uses two types of algorithms used here i.e.

1) Generative Algorithm: Predicts a label given certain features i.e. an outcome is assumed first and then find the relation between them.
2) Discriminative Algorithm: Maps features to labels i.e. classify the data into different categories.

The breakdown of the technology is as articulated in two parts i.e. the steps that GAN would take (keeping image as an example output) and a double feedback loop.

2.1 Basic Flow of GANs
1. The generator takes in random numbers and returns an image.

2. This generated image is fed into the discriminator alongside a stream of images taken from the actual, ground-truth dataset.
3. The discriminator takes in both real and fake images and returns probabilities, a number between 0 and 1, with 1 representing a prediction of authenticity and 0 representing fake.

The generator neural network (NN) generates new data instances. Whereas the discriminator NN evaluates their authenticity. In other words, the discriminator determines whether each instance of data that it examines belongs to the actual training dataset or not (genuine or fake).

2.2 Double Feedback Loop

The discriminator NN is in a feedback loop with the ground truth of the images (known to us). And the generator NN is in a feedback loop with the discriminator. The counterfeiter (or thief) and cop game is ordinarily used to explain this concept better. Both are dynamic i.e. both are learning and finding solutions of who is true and false on different situations.

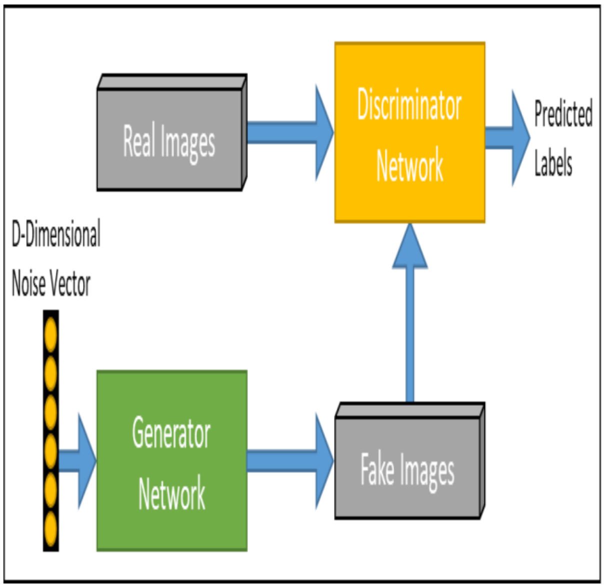

Fig. 1 A fundamental block diagram of GANs

Although here images are taken as an example data it can be any statistical or for that matter any appropriate input which has to either be tailored to become perfect or to generate something new out of the training data which should have the same framework but different content. [3]

3. INITIAL BOOST OF GANs

Interestingly, the kick start of the technology is reasonably recent i.e. in 2017 although its emergence was done with a novel paper by Ian Goodwill in 2014. The base ideas of the same sphere go back in the later 90s and Initial of 20th Century. Exact points of influence are discussed following this.

3.1 Adversarial Networks & Adversarial Curiosity (AC)

The network being discussed has two networks as its basis. One network uses probability for output generation, the other predicts output results. Every network minimizes the objective function which maximizes the other. Even on an intuitive level if one tries to analyze the structure and working of this technique it strongly shows its influence on GANs.

Table 1. Various concepts that spurred and influenced the emergence of the discussed technology. Following is the description of how each of them had their influences on GANs.

Date	Event / Concept Name	Acronym
1959	Adversarial Networks	-
1990	Adversarial Curiosity	AC
1996	Predictability Minimization	PM
2010	Noise-Contrastive Estimation	-
2013	Idea Similar to GANs	cGAN(given later on)
2014	Invention of Generative and Adversarial Networks	GANs
2017	Initial Boost of GANs	-

3.2 Predictability Minimization (PM)

Minimization of Predictability models conduct distributions of data through a neural encoder that maximizes objective function, minimized by a neural predictor. Interestingly, GANs technique is closely linked to PM in a statistical notion. Basically, both GANs and PM model data distribution statistics across gradient-adversarial networks that play a minimax game. This influence point under discussion also has controversial facets to it. The reasons for it are many including the claim that GANs is actually an extension or flavor of PM itself. [4]

3.3 Noise-Contrastive Estimation

This technique intriguingly throws light on the use of noise that GANs does. Noise Contrastive Estimation is defined as a way of learning a data distribution by comparing it against a noise distribution. This allows us to cast an unsupervised problem as a supervised logistic regression problem. Although the time difference between the invention of GANs and this one is comparatively less than others discussed prior to it.

Noise Contrastive estimation didn’t give efficient results because of which adversarial Contrastive Estimation, a general technique for improving supervised learning problems came which learns by contrasting observed and fictitious samples. Specifically, a generator network is used in a conditional GAN like setting to propose hard negative examples for our discriminator model. These are the factors which gave initial boost to GANs [5].

A new estimation theory, noise-contrastive estimation, consistently estimating complex mathematical models (specifically, statistic models) that need not be standardized (e.g., energy-based models or random fields of Markov).

3.4 Idea Similar to GANs

This is also known as the cGAN or conditional GAN now. Li, Gauci, and Gross used an idea close to GANs in 2013 to model animal behavior.

3.5 Invention of GANs

The most important influence for GANs was noise-contrast calculation, which utilizes the same loss method as GANs, and which Goodfellow researched during his PhD in 2010-2014. [6]

3.6 Initial Boost

In 2017, GAN was used for image enhancement with an emphasis on natural textures rather than pixel precision, allowing for better quality image output at high enlargement.

In 2017, the first faces were generated.

Starting in 2017, GAN technology attempted to make its presence felt in the fine arts field with the introduction of a newly developed application that was said to have passed the threshold of being able to generate unique and enticing abstract paintings and thus nicknamed the "CAN" for the "creative adversarial network"[7]. A GAN system was used to create the 2018 painting Edmond de Belamy, which sold for US$432,500 [8]. The early 2019 article by the members of the original CAN team discussed further progress with this system and then also considered the aggregate opportunities for AI-enabled art.

4. CLASSIFICATION

GANs has proved to be one of those technologies that has the potential to open-up doors towards for implementing the application traditional neural network or machine learning where constrained with. Below are some areas / industries where GANs has been applied and some example of each area they have been applied to. Following are the definitions of the classifications put forth:

- Image Domain: This domain of classification caters to applications concerning images of objects, things, people or any living or nonliving thing.
- Non-Image Domain: This domain of classification caters to applications which do not require images to process things.
- Hybrid Domain: Mixture of both image and Non-Image domain applications
- Translation: Applications which change (transfer) one thing to another thing
- Generation: Applications which generate new things using technology and do not translate one thing to another

The use of GANs although is not just restricted to the above mentioned areas. Since the very nature of the feature that GANs is capable of providing is very interesting variety of sectors are trying to make use of it in their B2B as well as B2C services.

Table 2. Classification Scheme of GANs Applications

Level 0	**Level 1**	**Level 2**	**Level 3**
Domain	**Application Type**	**Application**	**Sector**
Image Domain	Translation Type	Photos to Emojis	Entertainment
		Texture Synthesis	Entertainment
		Image-to-Image Translation	Fashion
		Clothing Translation	Fashion
		Semantic-Image-to-Photo Translation	Civil Engineering
		Text-to-Image Translation	Education
	Generation Type	Generate Photographs of Human Faces	Entertainment
		Face Aging	Entertainment
		Video Prediction	Entertainment
		Photograph Editing	Entertainment
		Generate Cartoon Characters	Entertainment
		Super Resolution	Entertainment
		Generate Realistic Photographs	Designing
		3D Object Generation	Designing
		Generate New Human Poses	Fashion
		Photo Inpainting	Archaeology
		Face Frontal View Generation	Crime
	Other Type	Photo Blending	Entertainment
		Anomaly Detection	Medical
Non-Image Domain	Generation Type	Music Generation	Music
Hybrid Domain	Other Type	Cross Domain Transfer	Biology

5. CONCLUSION

GANs is a technology that is here to stay for a lifetime until some other technology enables the same thing that GANs offers or any of its variants which applies everywhere where GANs could and provide even more beneficial output. After its initial boost in 2017, it has grown more and more both in terms of depth as well as breadth. In this paper, the authors have given a timeline showing the concepts that led towards the invention followed by the initial of GANs technology. It is found that noise-contrast measurement was the most important factor for GANs. Initial Boost in the context of this paper means a point in time that gave a kick start to the implementation of applications build using the discussed technology. Also, we've put forth a taxonomy for Applications of GANs. The Taxonomy is divided into Levels. The main three classifications come out to be Image Domain, Non-Image Domain, and Hybrid Domain. Then after other sub-classifications are also presented.

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