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Survey Paper on Applications of Generative Adversarial Networks in the Field of Social Media

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ABSTRACT
Social Media today is one of the most widely known terms. If the internet is the window to the world, social media is what actually has brought people from all over the world together. Today one can easily sit in the comfort of their homes and actively engage in an impactful political movement, taking place on the other end of the world. Social Media has enabled and impacted a myriad of fields. It has been a big aggressor in political movements, where candidates direct a major investment both in terms of time and money towards spreading the popularity of their campaign on social media websites. It has impacted major movements in recent times and brought out path-breaking societal changes. Social Media has provided companies with a new route of targeting their advertisements and has brought them closer to their customers and shareholders. Social Media has also opened up a new path of careers for many. Amongst all these positives, social media possess multiple challenges as well which include but are not limited to cyberbullying, privacy attacks and peer pressure which results in alarming rates of mental health detrition. The Generative Adversarial Nets is an extremely nascent but fast-growing network architecture in Deep Learning. This paper explores different forms of GANs and their applications in Social Media.

General Terms
Deep Learning, GANs

Keywords
GANs, Social Media, Deep Learning, DCGANS, StackGANs

1. INTRODUCTION
Generative Adversarial Networks is a deep learning, hierarchical model proposed by Ian Goodfellow et al. [1] as a revamped generative model to correct the challenges faced by deep generative models. In deep learning, discriminative models had seen huge successes as compared to generative models. GANs are a variation of generative models in which they introduced an adversary in the form of a discriminator. The purpose of the discriminator is to determine whether the sample produced by the generator is part of the model selection or data distribution. The network can be imagined as a game of struggle between the generator and discriminator. The generator can be imagined as a plagiarist with the aim of producing fake notes. The discriminator serves as a police officer with the aim of identifying and catching the fake notes. The generator at all times will try to pass the fake notes as real and the discriminator will try to stop that. Thus, this competition between the two will cause the generator to produce samples that are as similar-looking and indistinguishable from the real ones.

The GANs follow a min-max zero-sum game played between the generator and discriminator. The generator is tasked with producing the fake samples. The discriminator shows the probability of the likelihood of the sample is similar to the real sample. A probability of 0.5 is ideal as any smaller probability indicates the sample being counterfeit while a probability of 1 indicates that the fake sample is, in fact, a real sample, thus failing its purpose.

1. Generator: The generator is a network used to produce fake samples using the random noise vector. It is represented by G and the generated samples as G(z). The noise is the parameter producing the fake images in latent space.

2. Discriminator: The discriminator network receives the fake samples and the real training sample as an input. The aim of this discriminator is to check whether the fake samples are similar to the real input. The discriminator gives a probability of 0 if they are not the same and a probability of 1 if they are the same. It is represented as D. The discriminator is a convolutional neural network.

The parameters G and D are both updated parallelly during the entire process.

The components of the above architecture can be shown in the fig 1.

2. TYPES OF GANS
GANs throughout the years have seen a wave of development and evolution. To fit various application areas their architecture has been varied. This section aims to highlight the few types of GANs that find a popular spot in the usage in practical applications.

2.1 Fully Connected GAN
The fully connected GAN was the original network produced by the first paper which was trained on simpler datasets such as the MNIST dataset, CIFAR and Toronto Face Dataset

2.2 Deep Convolutional GANs
The above fully connected GANs represented a simple feed-forward network with a single hidden layer that was unable to produce recognizable images of handwritten digits modelled from the MNIST dataset. So, to increase its computational power to produce more realistic images, Radford et al. [2] were able to implement the Generator and Discriminator as a rich convolutional network. The pooling layers for the generator consisted of fractional sided convolutions, while for the discriminator it consisted of stridden convolutions.

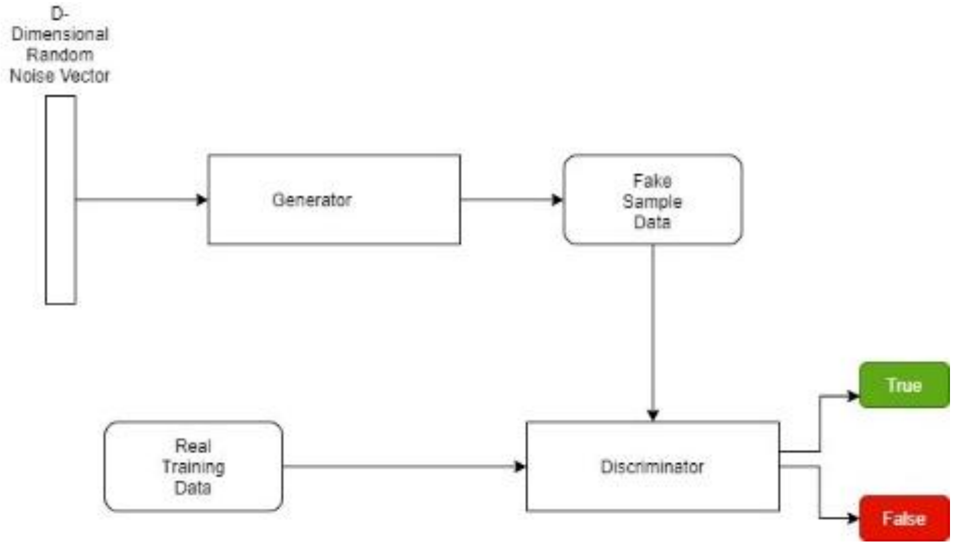

Fig 1: The architecture of the basic Generative Adversarial Network

They were then able to introduce optimization techniques that allowed the network to use scaled up ConvNets without actually changing the base architecture. The usage of batch normalisation added to each mini epoch stabilised the learning by normalising each input to unit variance.

The above type of GAN was applied on the LSUN bedroom dataset as well as on faces scraped from the web and ImageNet.

2.3 Conditional GANs

Mirza et al. [3] propose to focus on using conditions to be able to navigate the output of GANs. To formulate this condition to the network the paper adds an extra conditional information y to both generator and discriminator networks. The extra information y can be any auxiliary information and is defined as an extra input layer for both generators and the discriminator.

In the generator network, the conditional y information is combined with the noise vector as a joined hidden representation, while in the discriminator network y is fed as input alongside the real training data.

2.4 Stack GANs

With the intent of conditionalGANs, the research areas for GANs and its applicants found a new dawn. StackGANs is such an invention that allows GANs to generate photo-realistic images from text descriptions. Han Zhang et al [4] proposes the form of a stacked architecture of GANs which can be classified as a two-stage and multi-stage architecture. The paper aims at an output of a 256x256 photo-realistic image.

The above paper, apart from its unique arrangement and use of multiple GANs also proposes a new technique of conditioning augmentation training that imparts stability to the training process as well as imparts diversity in the produced training samples. The idea behind the introduction of the conditioning augment is to avoid the use of a constant condition *c* and use a randomly generated condition directly from the text embeddings.

The two-stage generators are divided into Stage 1 and Stage 2 GANs.

Stage 1 GAN: The Stage 1 GAN is mainly responsible for sketching a primitive shape and basic colour scheme onto the image. It takes the text embedding as an input along with the random noise vector producing a 64×64 image which is low in quality. The output from stage 1 GAN is fed into stage 2 GAN.

Stage 2 GAN: The Stage 2 GAN receives the text embedding and the output of the stage 1 GAN i.e. the low quality 64x64 image and then corrects the defects of the stage 1 GAN and adds details using the text embedding to produce photorealistic images. The proposal of StackGANs [4] is advantageous as it allowed visuals of higher resolution to be generated with conditional GANs. The conditioning augment module allows conditional smoothening, that is it focuses on the details of the image as well

3. APPLICATION OF GANs IN SOCIAL MEDIA

3.1 Fake News Detection

Fake news or fabricated pieces of information planted by organisations and corporations under the disguise of genuine news is a concern amongst the exponential growth and reach of social media in the society. Evidence and studies suggest that social media has had a strong impact on the way people make decisions. Often before entering into a consumerism transaction, people will tend to read the reviews, looking at both the positives and negatives. Fake news or even misdirected news are planted to affect the mind of voters, often swinging national elections.

Efforts have been strong within the machine learning community in order to tackle this menace. Abdullah-All-Tanvir et al. [5] use 5 machine learning classification algorithms such as Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, long short-term memory, Recurrent Neural Networks to detect fake news. Algorithms such as Naive Bayes and SVM performed the best at 89% followed by deep learning algorithms such as LSTMs and RNNs at 73-74%. However, a major drawback of using these algorithms is that the techniques are all supervised learning techniques and hence for a greater accuracy would require a huge labelled sample data. With textual data the lack of available data questions the practicality of these algorithms. Thus, arises a need to solve this problem using unsupervised learning or semi-supervised learning algorithms.

To tackle this problem various researches are putting effort into using GANs for identifying deceptive news and reviews. Srinidhi Hiriyannaiah et al. [6] proposes the use of SeqGAN to identify fake news. A framework is proposed in which GANs can be tasked to produce data. GANs are a two-player min-max game played between the generator and discriminator. The generator is always trying to generate realistic but fake content. This same property is being proposed as the main use case of GANs in this problem. The paper proposes that the GAN be trained to produce text data which essentially would be headlines or news snippets, which would be counterfeit articles. Thus these 'fake' news can now be mixed with the real news data and used to train a deep neural network thus aiding better accuracy to detect fake news. For this task, the paper uses SeqGANs [7].

Another major field where the use of GANs can be countered towards detecting deceptive news. Hojjat Aghakhani et al. [8] proposes a new network called FakeGAN which can run to detect any deceptive reviews. For the task, the paper uses the TripAdvisor data for hotels. Normally GANs work on the principle of creating a strong generator, but FakeGANs rely on creating a strong discriminator. Thus, the paper uses two discriminators D and D' and one generator G. FakeGANs are inspired by SeqGANs and are focussed on text data generation. The generator here is used as a stochastic agent for reinforcement learning and the RL reward is provided by the discriminator which uses the Monte Carlo heuristic search algorithm. The training data contains two types of reviews both the real review and the fake review. The parameterized generator produces the review S as a sequence of tokens. The discriminator D produces a probability indicating whether the current sample belongs to truthful reviews or to either the fake reviews generated by both the generator and the ones available in the training dataset. The discriminator D' indicates whether the fake review is generated by the GAN network or already present in the dataset. Thus using the feedback generated from D and D'. the generator will be able to generate a review which is both deceptive to D' and truthful to D.

When trained and tested on the TripAdvisor dataset, FakeGANs, a semi-supervised method, showed an accuracy of 89.2% and state of the art supervised learning algorithms showed 89.8% accuracy. This close enough accuracy calls for more research and more scope for GANs being used to generate and detect discrete data items such as text.

3.2 Advertising in Social Media

Advertising on social media has opened up a new arena of revenue generation. Companies of variable sizes and of variable agendas are looking at social media sites in order to extend their product reach. From a home-based venture to a multinational company, a lot of marketing models are dependent upon social media to advertise their product. Sites such as Amazon, eBay have opened up new peer to peer markets where the customer can interact with the product directly. Thus, in these times, it is essential that the company develops content, both in form of images as well as texts, in order to push their company on such competitive websites. GANs are known to be used to generate data. Hence in this section, the use of such generative adversarial nets in terms of advertising and marketing on Social Media using image and text-based content is explored.

A case study of Airbnb by Richard Diehl Martinez et al. [9] explores the use of GANs in marketing. It suggests the use of GANs to suggest ways to frame text descriptions so that it increases the probability of the listing being booked. This method has initially been deployed on the Airbnb dataset, but the framework can be used in any peer to peer marketplace.

For the intended task, the paper suggests using the data of a particular listing in a given location for a stipulated period of time, which is used as the primary data. On the basis of the price, occupancy rate the GAN classifies the listings on a scale of popularity of classes low, medium or high. The paper then creates a network of RNN with LSTM gates useful for predicting the popularity of a given rating. The input is the text embeddings which have been converted into GloVe vectors. The output of this forms the core data for the use in the GAN network. The GAN architecture proposed below shows how the network will be able to replicate descriptions to fit popular descriptions.

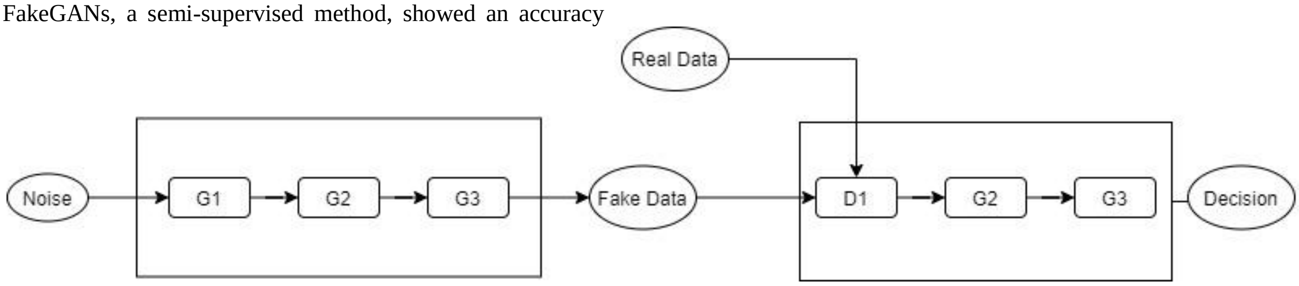

Fig. 2 Architecture for the 3-layer deep feedforward network used in Airbnb Case study

The generator is proposed as a 3-layer deep feed-forward network that receives a random noise vector Z as the input. The output of the generator module then produces fake data. The discriminator module is also a three-layer deep feed-forward structure that aims to discriminate between the real and fake data. The real data is received from the listings classified as 'popular' by the RNN/LSTM network. Thus, the generator will always try to produce data similar to the 'popular' real data and discriminator will try to discriminate between the two. The experiment shows an accuracy of 40%. The unsupervised learning module adds an advantage to the structure being used in advertising and marketing to better their outreach.

For an image-based generation of photo-realistic images, the initial model proposed by Radford et al. [2] of the DCGANs aims to generate stock photo images. Using Deep Conditional GANs they were successfully able to produce photos of 28x28 pixels. However, the low quality of these images is a concern. Hence new methods have been proposed to improve the same.

Nets such as LAPGAN [10] are based on the Laplacian Pyramid in which at each layer learning between the residual layers is learnt and this helps stack up multiple low-level images into a higher-level image. Various other GAN structures are being explored to develop stock photos.

With Pose Guided Image Generation proposed by Liqian Ma et al. [11], poses of images can be changed and configured. This finds use in fashion-based e-commerce websites and advertising campaigns used to display all sides of a given product. PoseGAN aims to change the pose of the object of an image with respect to the pose of a target image. The paper proposes this task and shows how this difficult change can be possible using various methods. The network proposed contains two generators and one discriminator. The Stage 1 generator inputs the target pose and the image to be conditioned on and outputs a general structure of the human. The second generator using the generator and the adversarial module focuses on refining the image and the coarse details of the posture.

Stage 1: The first stage contains 3 components - Pose Embedding, Generator 1, Pose Mask Loss. Pose Embedding is used to approximate the human pose by

CycleGAN [12] and StarGAN[13] aid in the conversion of an image from one domain to another allowing the user to view different variations of the same product. PixelDTGAN [14] finds its use in e-commerce as it can suggest clothing and styles based out of an image.

3.3 PassGANs for password detection and strong password suggestion

Passwords and Usernames form an integral aspect of social media interaction. In days and age where data is considered a commodity, it is extremely essential that one must protect one's intimate data from personal attacks. Thus, it is always important to maintain the use of strong passwords. Suggested by Briland Hitaj et al. [15], this paper proposes the construction of a PassGAN that can be used to predict a given password. While many such password cracking algorithms exist, many of them are devised around a set of rules for predicting passwords, thus might be unable to detect complex patterns. PassGAN is based on an improvement of WGANs [16] and they contain a generator and discriminator.

The generator takes the random noise as input and passes it through the residual blocks to generate a fake password. The discriminator tries to guess the fake password from the real passwords from the training dataset and provides feedback to the generator which on the basis of the feedback from the generator finetunes its parameters. When trained on the RockYou dataset, the test accuracy of PassGAN to match or predict passwords is 34.2%. This model when augmented with deep learning password generating algorithms can defeat the state-of-the-art model guesses.

In April 2013, it was reported that almost 6 million+ passwords were stolen from LinkedIn and 32 million + passwords were stolen from RockYou dataset. Thus, to tackle this the concept of Honeywords is used. Honeywords are words similar to a user-selected password present in a stolen password file. Presence of Honeywords makes it hard for the attacker to decode the true password, hence adding an additional layer of protection. Thus, PassGANs can be used to generate Honeywords, which must not be too similar to the username or the user-selected password, but confusing enough to prevent detection of the real password. Thus, protecting data in a competitive social media environment.

Another major application area for PassGANs is suggesting stronger passwords. When a password is entered, the model runs to check the strength and predicts the probability of the user entering the password to be detected. Hence through the above, applications, the use of GANs in order to protect data on social media is seen.

3.4 GANs for Image Filtering and Tweaking Detection

An important aspect of image-based social media sites is the tweaking of images to create and form different forms. GANs work in special ways. From tweaking the images to attribute manipulation to forming caricatures, GANs can be used in social media to create new images from existing ones. This section is aimed at exploring the concept of AttGAN [17] that can be used for facial attribute editing to change only what is required.

AttGAN derives its basics from the IcGAN [18] and Fader networks [19], however unlike the above two nets, AttGAN focuses on changing only the concerning attributes. Supervised Learning for these tasks is shown to fail because it is impossible to create a labelled dataset of people with the same attributes, hence unsupervised and semi-supervised learning techniques such as this come into play. There exist two main subnets for the generator: the encoder and decoder, the attribute classifier and the discriminator.

The intended image with the attributes serves as an input to the encoder generator which creates the latent representation of the attributes. This is then fed to the two decoder generators. The first decoder contributes to the process of editing of the image and the second decoder will contribute to maintaining the other attributes and structure of the original image.

The first decoder is connected to the attribute classifier which is used to constrain the generated image from the generator encoder to correctly identify its own desired attributes and the discriminator makes sure that the realities of the image are maintained. The second decoder is connected back to the encoder to maintain reconstruction learning which helps conserve the information of the images which haven't undergone attribute editing.

Apart from the example of the above AttGAN, various other methodologies like StyleGANs [21], PCGANs [20] are and can be used to create and change styles for an image. Image inpainting is another technique that is employed to be able to tweak an image to remove unnecessary objects without tampering with the overall image. This application is extremely impressive in today's social media world as it would reduce strain on a lot of editing applications. GANPaint [22], a collaborative project between MIT and IBM showed that as per user command, the model can paint or erase specific features of the image.

A counter to the above application is the detection of edited images. This field of research is known as image forensics which has a wide base in all areas of machine learning. With the idea to approach a real-world even on social media, many popular organizations such as Instagram are taking steps in order to contain edited images. Image Forensics aims at identifying and generalising the patterns of such edited images as well as identifying such artificially generated images. Efforts to identify images generated by GANs using GANs was proposed by Xinsheng Xuan et al. [23]. They trained a deep neural network of CNNs on PG-GANs [24] to infer the results of DCGAN [2]/WGANs [16]. However, there was an absence of patterns showing that the forgeries committed by one type of GAN were not similar to another type. Thus, research to detect tweaked, edited or artificially generated images using GANs is still in the early stages.

Table 1. Applications and the corresponding GAN used

Application	Type of GANs used
Fake News Detection	SeqGAN
	FakeGAN
Advertising in Social Media	DCGAN
	LAPGAN
	PoseGAN
	CycleGAN
	StarGAN
	PixelDTGAN
Password Detection	PassGAN
Image Filtering and Detection	AttGAN
	IcGAN
	Fader Network
	StyleGAN
	PCGANs
	GANPAINT

4. MAJOR CHALLENGES

The above applications highlight the domain adaptation for Generative Adversarial Networks since the lack of labelled data can be overcome by using this semi-supervised learning technique. However, the use of GANs comes with a lot of red tapes. Few of the applications highlighted above make the use of text as data for GANs. Text is a type of discrete data, unlike images which are continuous. As shown in this paper GANs work by propagating gradients through the generator and discriminator, while the text is generated as a probability of generating the next stochastic unit. The above two methods don't gel well together, hence the applications of GANs involving text-based data, are still not adaptable to practical working. Another challenge posed by GANs is stability. Thus, while adapting GANs to a practical application, it is important to make sure that the model is stable and the outputs produced are not too different.

5. CONCLUSION

This paper comprehensively shows the aim and applications of GANs. This paper describes the various popular types of GANs available today and how they correlate and are applicable to social media. This paper studies the different categories and areas that these applications can be applied and how they will affect society today. Lastly, this paper highlights the challenges faced today by GANs and their applications in the real world.

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