**Critical Analysis:**

**Generative Adversarial Nets**

To overcome the inability of Deep generative models in approximating many intractable probabilistic computation, Ian J. Goodfellow came up with the idea of Adversarial nets which was the start of advancement in the field of image, video and voice generation. The paper was published by Ian and co-authors on 10 JUN 2014. In this article they explored the special case when the generative model generates samples by passing the random noise through a multilayer perceptron and the discriminative model is a multilayer perceptron. The generative network is trained to maximise the classification error. The discriminative network is trained to minimize the final classification error. The classification error is the reference metric for the training of both the networks. Both the models are trained using backpropagation and dropout algorithm and sample from the generative model using only forward propagation. In case of Forward propagation, they use generator to generate fake data from random inputs and use discriminator to separate the true data from the fake data. In case of Backward propagation, they update discriminator weight to decrease the classification error and update generator weight to increase the classification error.

Since the publication there have been many developments in this filed. The first would be introduction of DCGAN [1] which used transposed convolution operation which helps to transform low-resolution images into higher resolution ones. The use of multiple of these transposed layers allow us to change low resolution into vibrant colour image. In further development CoGAN [2] was introduced which uses two GAN instead of one. The motive for this type of network was to learn a joint distribution without any tuple of corresponding images and we get two images at the cost of one and half.

ProGAN [2] is a technique that helps stabilize GAN training by incrementally increasing the resolution of the generated image. The later progress made were introduction of new algorithm named WGAN [2] which focused on traditional GAN training. It showed to improve the learning stability and researchers also provided theoretical insights highlighting deep connections to other distances between distributions.

Furthermore, recent work has shown that generator conditioning affects GAN performance and SAGAN [4] was put forward by Zhang han, which allows attention-driven, long-range dependency modelling for image generation tasks. Leveraging this insight, they have applied spectral normalization to the GAN generator and find that this improves training dynamics.

Foremost the best development to GAN was BigGAN[6] which is an approach to pull together a suite of recent best practices in training class-conditional images and scaling up the batch size and number of model parameters. The result is the routine generation of both high-resolution and high-quality images. The last but not the least on these developments is styleGAN [7] which focuses on improving the existing GAN capabilities. StyleGAN focuses on loss functions, stabilization, architectures and other aspects.

Addition to these there were multiple techniques were introduced where the input variables were enhanced. CGAN [8] was introduced to solve the issue where the generator is told to generate only one class of images. In GAN there was issue with the problem called as image-to-image translation, CycleGAN [9] was introduced to overcome this issue where they presented an approach for learning to translate an image from a source domain to a target domain in the absence of paired examples.

We have discussed certain new published works over the GAN now let’s discuss about what these have brought improvement over the original work. CoGAN improves the cost, memory and storage as fewer parameters were used and the network was not too much complicated as the weights were similar for some layers. The GAN was generating data from random noise and can mix the images of different classed. CGAN acronym for conditional generative adversarial network focuses to solve the issue by telling the generator to generate images of only one class. There are many problems with training GANs. The most important of which is the training instability which ProGAN helped to both speeds the training up and greatly stabilizes it which helps to produce the images of great quality. WGAN [4] get rid of problems like mode collapse and provide meaningful learning curves useful for debugging and hyperparameter searches. Traditional convolutional GANs generate high-resolution details as a function of only spatially local points in lower-resolution feature maps. In SAGAN [5], details can be generated using cues from all feature locations. Despite recent progress in generative image modeling, successfully generating high-resolution, diverse samples from complex datasets was elusive goal which was achieved by using BigGAN. The new generator improves the state-of-the-art in terms of traditional distribution quality metrics, leads to demonstrably better interpolation properties, and better disentangles the latent factors of variation. StyleGAN improves a GANs capability to have fine control over the image that’s generated rather than focusing on creating more realistic images.

As per the paper published in corresponding years the interesting remaining problem in GAN is still missing very fine-grained control. One of the issues described when training BigGAN generators is the idea of “class leakage”, a new type of failure mode. Also, BigGANs do not capture the ImageNet data distributions and are only modestly successful for data augmentation. Also, the field has been highly developed on an extent that the GAN generated content will become increasingly difficult to distinguish from real content. So, new ways and research methods is the need of the hour to identify between real and fake.

The GAN works well with the continuous data, but the unsolved issue is how well GAN can perform on non-image data or in other words other non-continuous data like text, audio etc. The question here is does scaling GANs to other domains require new training techniques, or does it simply require better implicit priors for each domain. There have been approaches where both generator and discriminator with reinforcement learning, but it requires high computational resources. Hence this needs further fundamental research progress.

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