A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications

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Abstract—Generative adversarial networks (GANs) have recently become a hot research topic; however, they have been studied since 2014, and a large number of algorithms have been proposed. Nevertheless, few comprehensive studies explain the connections among different GAN variants and how they have evolved. In this paper, we attempt to provide a review of the various GAN methods from the perspectives of algorithms, theory, and applications. First, the motivations, mathematical representations, and structures of most GAN algorithms are introduced in detail, and we compare their commonalities and differences. Second, theoretical issues related to GANs are investigated. Finally, typical applications of GANs in image processing and computer vision, natural language processing, music, speech and audio, the medical field, and data science are discussed.

Index Terms—Deep learning, generative adversarial networks, algorithm, theory, applications

1 Introduction

Generative adversarial networks (GANs) have recently become a hot research topic. Yann LeCun, a legend in deep learning, said in a Quora post "GANs are the most interesting idea in the last 10 years in machine learning." According to Google Scholar, a large number of papers related to GANs already exist. For example, approximately 28,500 papers related to GANs were published in 2020, constituting approximately 78 papers every day or more than three per hour.

GANs consist of two models: a generator and a discriminator. These two models are typically implemented using neural networks but could be implemented using any form of differentiable system that maps data from one space to another. The generator tries to capture the distribution of true examples and generate new data examples. The discriminator is usually a binary classifier used to discriminate generated examples from true examples as accurately as possible. The optimization of GANs is a minimax optimization problem. The optimization terminates at a saddle point that forms a minimum with respect to the generator and a maximum with respect to the discriminator. That is, the GAN optimization goal is to reach Nash equilibrium [1]. At that point, the generator can be considered to have accurately captured the distribution of real examples.

Some previous works adopted the concept of making two neural networks compete with each other. The most relevant works are adversarial curiosity [2], [3], [4] and predictability minimization [5]. The connections among adversarial curiosity, predictability minimization, and GANs can be found in [6], [7].

The popularity and importance of GANs have led to several previous reviews. The difference between this study and previous works is summarized below.

1) *GANs for specific applications*: Some surveys have targeted the use of GANs for specific applications, such as image synthesis and editing [8], text-to-image synthesis [9], and audio enhancement and synthesis [10].
2) *General surveys*: The earliest relevant review was probably the paper by Wang *et al.* [11], which introduced the progress in GANs before 2017. Others [12], [13] mainly covered the progress in GANs prior to 2018. The authors of [14] introduced architecture variants and loss variants of GANs related only to computer vision. Other related works can be found in [15], [16].

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TABLE 1
Overview of GAN Algorithms Discussed in Section 3

GANs Representative variants		InfoGAN [17], cGANs [18], CycleGAN [19], f-GAN [20], WGAN [21], WGAN-GP [22], LSGAN [23]
GANs training	Objective function	LSGANs [24], [25], hinge loss based GANs [26]–[28], MDGAN [29], unrolled GAN [30], SN-GANs [26], RGANs [31]
	Skills	ImprovedGANs [32], AC-GAN [33]
	Structure	LAPGAN [34], DCGANs [35], PGGAN [36], StackedGAN [37], SAGAN [38], BigGANs [39], StyleGAN [40], hybrids of autoencoders and GANs (EBGAN [41], BEGAN [42], BiGAN [43]/ALI [44], AGE [45]), multi-discriminator learning (D2GAN [46], GMAN [47]), multi-generator learning (MGAN [48], MAD-GAN [49]), multi-GAN learning (CoGAN [50])

TABLE 2
Applications of GAN Algorithms Discussed in Section 5

Field	Subfield	Method
Image processing and computer vision	Super-resolution	SRGAN [51], ESRGAN [52], Cycle-in-Cycle GANs [53], SRDGAN [54], TGAN [55]
	Image synthesis and manipulation	DR-GAN [56], TP-GAN [57], PG^2 [58], PSGAN [59], APDrawingGAN [60], IGAN [61], introspective adversarial networks [62], GauGAN [63]
	Texture synthesis	MGAN [64], SGAN [65], PSGAN [66]
	Object detection	Segan [67], perceptual GAN [68], MTGAN [69]
	Video	VGAN [70], DRNET [71], Pose-GAN [72], video2video [73], MoCoGan [74]
Sequential data	Natural language processing (NLP)	RankGAN [75], IRGAN [76], [77], TAC-GAN [78]
	Music	RNN-GAN (C-RNN-GAN) [79], ORGAN [80], SeqGAN [81]

To the best of our knowledge, this paper is the first to provide a comprehensive survey of GANs from algorithm, theory, and application perspectives that covers recent progress. Furthermore, our paper focuses on applications related not only to image processing and computer vision but also to sequential data such as natural language processing and to related areas such as the medical field.

The remainder of this paper is organized as follows. The related works are discussed in Section 2. Sections 3–5 introduce GANs from the algorithm, theory, and application perspectives. Tables 1 and 2 list the main GAN algorithms and application fields, which are discussed in Sections 3 and 5, respectively. Finally, Section 6 concludes the survey.

2 Related Work

GANs belong to a class of generative algorithms. Generative algorithms and discriminative algorithms are two categories of machine learning algorithms. Approaches that explicitly or implicitly model the distributions of inputs as well as outputs are known as generative models [82]. Generative algorithms have become increasingly popular and important due to their wide practical applications.

2.1 Generative Algorithms

Generative algorithms can be classified into two classes: explicit density models and implicit density models.

2.1.1 Explicit Density Models

An explicit density model defines a probability density function $p_{model}(x;\theta)$ and utilizes true data to fit the parameters θ. After training, new examples are produced utilizing the trained model or distribution. The explicit density models include maximum likelihood estimation (MLE), approximate inference [83], [84], and the Markov chain method [85], [86], [87]. These explicit density models use an explicit distribution and have limitations. For instance, MLE is conducted on true data, and its parameters are directly updated based on the true data, which leads to an overly smooth generative model. The generative model learned by approximate inference only approaches the lower bound of the objective function rather than directly solving the objective function because of difficulties involved in solving the objective function. The Markov chain algorithm can be used to train generative models, but it is computationally expensive. Furthermore, explicit density models have a computational tractability problem because they may fail to reflect the complexity of the true data distribution and learn the high-dimensional data distributions [88].

2.1.2 Implicit Density Models

An implicit density model does not directly estimate or fit the data distribution; instead, it produces data instances from the distribution without an explicit hypothesis [89] and utilizes the produced examples to modify the model. Prior to GANs, the implicit density model generally needs to be trained utilizing either ancestral sampling [90] or Markov chain-based sampling, which is inefficient and limits their practical applications. GANs belong to the directed implicit density model category. A detailed summary and relevant papers can be found in [91].

2.1.3 Comparison of GANs and Other Generative Algorithms

GANs were proposed to overcome the disadvantages of other generative algorithms. The basic idea behind adversarial learning is that the generator tries to create examples that are as realistic as possible to deceive the discriminator, while the discriminator tries to distinguish the generated fake examples from true examples. Both the generator and discriminator are improved through adversarial learning. This adversarial process gives GANs notable advantages over other generative algorithms. The specific advantages of GANs over other generative algorithms are as follows.

1) GANs can parallelize generation across a single large image, which is difficult for other generative algorithms such as the pixel convolutional neural network (PixelCNN) [92] and fully visible belief networks (FVBNs) [93], [94].
2) The generator design has few restrictions.
3) GANs are subjectively thought to produce better examples than those produced by other methods.

Refer to [91] for more detailed discussions about these comparisons.

2.2 Adversarial Idea

The adversarial idea has been successfully applied in many areas, including machine learning, artificial intelligence, computer vision and natural language processing. The 2016 defeat of the world's top human Go player by the AlphaGo model [95] engaged public interest in artificial intelligence. The intermediate version of AlphaGo utilizes two networks that compete with each other.

Adversarial examples [96], [97], [98], [99], [100], [101], [102], [103], [104], [105] also involve the adversarial idea. Adversarial examples are examples that differ substantially from real examples but are classified into a real category with high confidence or examples that differ only slightly from the real examples but are misclassified. This has recently become a very hot research topic [100], [101]. To prevent adversarial attacks [106], [107], [108], [109] utilized GANs to conduct the correct defense.

Adversarial machine learning [110] is a minimax problem in which a defender, who builds the classifier that we want to work correctly, searches over the parameter space to find the parameters that reduce the cost of the classifier as much as possible. Simultaneously, the attacker searches over the model inputs to maximize the cost.

Adversarial ideas can be found in adversarial networks, adversarial machine learning, and adversarial examples. However, they have different objectives.

3 Algorithms

In this section, we first introduce the original GANs followed by their representative variants and training.

3.1 GANs

The GAN framework is straightforward to implement when the models are both neural networks. To learn the generator distribution p_g over data x, a prior on input noise variables is defined as $p_z(z)$ [6], where z is the noise variable. Then, the generator represents a mapping from noise space to data space as $G(z, \theta_g)$, where G is a differentiable function represented by a neural network with parameters θ_g. The other neural network, $D(x, \theta_d)$, is also defined with parameters θ_d, but the output of $D(x)$ is a single scalar. $D(x)$ denotes the probability that x comes from the data rather than from the generator G. The discriminator D is trained to maximize the probability of assigning a correct label to both real training data and fake examples generated by the generator G. Simultaneously, G is trained to minimize $\log(1 - D(G(z)))$.

3.1.1 Objective Function

Different objective functions can be used in GANs.

3.1.1.1 Original minimax game: The objective function of GANs [6] is

$$\min_G \max_D V(D, G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))]. \tag{1}$$

where $\log D(x)$ is the cross-entropy between $[1 \quad 0]^T$ and $[D(x) \quad 1 - D(x)]^T$. Similarly, $\log(1 - D(G(z)))$ is the cross-entropy between $[0 \quad 1]^T$ and $[D(G(z)) \quad 1 - D(G(z))]^T$. For a fixed G, the optimal discriminator D [6] is given by

$$D_G^*(x) = \frac{p_{data}(x)}{p_{data}(x) + p_g(x)}. \tag{2}$$

The minimax game in (1) can be reformulated as

$$\begin{aligned} C(G) = &\max_D V(D, G) = E_{x\sim p_{data}}\left[\log D_G^*(x)\right] \\ &+ E_{z\sim p_z}\left[\log\left(1 - D_G^*(G(z))\right)\right] \\ &= E_{x\sim p_{data}}\left[\log D_G^*(x)\right] + E_{x\sim p_g}\left[\log\left(1 - D_G^*(x)\right)\right] \\ &= E_{x\sim p_{data}}\left[\log \frac{p_{data}(x)}{\frac{1}{2}\left(p_{data}(x) + p_g(x)\right)}\right] \\ &+ E_{x\sim p_g}\left[\frac{p_g(x)}{\frac{1}{2}\left(p_{data}(x) + p_g(x)\right)}\right] - 2\log 2. \end{aligned} \tag{3}$$

The Kullback–Leibler (KL) divergence and the Jensen-Shannon (JS) divergence between two probabilistic distributions $p(x)$ and $q(x)$ are defined as follows:

$$KL(p\|q) = \int p(x)\log\frac{p(x)}{q(x)}dx, \tag{4}$$

$$JS(p\|q) = \frac{1}{2}KL\left(p\|\frac{p+q}{2}\right) + \frac{1}{2}KL\left(q\|\frac{p+q}{2}\right). \tag{5}$$

Therefore, (3) is equal to

$$\begin{aligned} C(G) &= KL\left(p_{data}\|\frac{p_{data}+p_g}{2}\right) + KL\left(p_g\|\frac{p_{data}+p_g}{2}\right) - 2\log 2 \\ &= 2JS(p_{data}\|p_g) - 2\log 2. \end{aligned} \tag{8}$$

Thus, the objective function of GANs is related to the JS divergence.

3.1.1.2 Non-saturating game: In some cases, Eq. (1) may not provide a sufficient gradient for G to learn well. Generally, G is poor during early learning, and the generated examples clearly substantially differ from the training data. Therefore, D can reject these early generated examples with high confidence. In this situation, $\log(1 - D(G(z)))$ saturates. However, we can train G to maximize $\log(D(G(z)))$ rather than minimize $\log(1 - D(G(z)))$. The cost for the generator then becomes

$$\begin{aligned} J^{(G)} &= E_{z\sim p_z(z)}[-\log(D(G(z)))] \\ &= E_{x\sim p_g}[-\log(D(x))]. \end{aligned} \tag{7}$$

This new objective function results in the same fixed point in the dynamics of D and G but provides much larger gradients during the early learning process. The non-saturating game is heuristic and is not motivated by theory. However, the non-saturating game has other problems, such as an unstable numerical gradient for training G. With the optimal D_G^*, we have

$$\begin{aligned} &E_{x\sim p_g}\left[-\log\left(D_G^*(x)\right)\right] + E_{x\sim p_g}\left[\log\left(1-D_G^*(x)\right)\right] \\ &= E_{x\sim p_g}\left[\log\frac{\left(1-D_G^*(x)\right)}{D_G^*(x)}\right] = E_{x\sim p_g}\left[\log\frac{p_g(x)}{p_{data}(x)}\right] \\ &= KL(p_g\|p_{data}). \end{aligned} \tag{8}$$

Therefore, $E_{x\sim p_g}\left[-\log\left(D_G^*(x)\right)\right]$ is equal to

$$\begin{aligned} &E_{x\sim p_g}\left[-\log\left(D_G^*(x)\right)\right] \\ &= KL(p_g\|p_{data}) - E_{x\sim p_g}\left[\log\left(1-D_G^*(x)\right)\right]. \end{aligned} \tag{9}$$

From (3) and (6), we have

$$\begin{aligned} &E_{x\sim p_{data}}\left[\log D_G^*(x)\right] + E_{x\sim p_g}\left[\log\left(1-D_G^*(x)\right)\right] \\ &= 2JS(p_{data}\|p_g) - 2\log 2. \end{aligned} \tag{10}$$

Therefore, $E_{x\sim p_g}\left[\log\left(1-D_G^*(x)\right)\right]$ equals

$$\begin{aligned} &E_{x\sim p_g}\left[\log\left(1-D_G^*(x)\right)\right] \\ &= 2JS(p_{data}\|p_g) - 2\log 2 - E_{x\sim p_{data}}\left[\log D_G^*(x)\right]. \end{aligned} \tag{11}$$

By substituting (11) into (9), (9) reduces to

$$\begin{aligned} &E_{x\sim p_g}\left[-\log\left(D_G^*(x)\right)\right] \\ &= KL(p_g\|p_{data}) - 2JS(p_{data}\|p_g) \\ &\quad + E_{x\sim p_{data}}\left[\log D_G^*(x)\right] + 2\log 2. \end{aligned} \tag{12}$$

From (12), we can see that optimizing the alternative G loss in the non-saturating game is contradictory because the first term aims to minimize the divergence between the generated distribution and the real distribution while the second term aims to maximize the divergence between these two distributions due to the negative sign. This results in an unstable numerical gradient when training G. Furthermore, the KL divergence is not a symmetrical quantity, as reflected by the following two examples:

- If $p_{data}(x)\to 0$ and $p_g(x)\to 1$, we have $KL(p_g\|p_{data})\to +\infty$.
- If $p_{data}(x)\to 1$ and $p_g(x)\to 0$, we have $KL(p_g\|p_{data})\to 0$.

The penalties for the two types of errors made by G are completely different. The first error type occurs when G produces implausible examples, which results in a large penalty. The second error type occurs when G does not produce real examples, and the penalization is quite small. The first error type involves generated examples that are inaccurate, while the second error type involves insufficiently diverse generated examples. Based on this, G will prefer to produce repetitious but safe examples rather than risk producing different but unsafe examples. This problem is termed the mode collapse problem.

3.1.1.3 Maximum likelihood game: Many methods exist to approximate (1) in GANs. Under the assumption that the discriminator is optimal, minimizing

$$\begin{aligned} J^{(G)} &= E_{z\sim p_z(z)}\left[-\exp\left(\sigma^{-1}(D(G(z)))\right)\right] \\ &= E_{z\sim p_z(z)}[-D(G(z))/(1-D(G(z)))], \end{aligned} \tag{13}$$

where σ is the logistic sigmoid function, is equal to minimizing (1) [111]. A demonstration of this equivalence can be found in Section 8.3 of [91]. Furthermore, there are other possible ways of approximating maximum likelihood within the GAN framework [20]. A comparison of the original zero-sum game, non-saturating game, and maximum likelihood game is shown in Fig. 1.

Three observations can be obtained from Fig. 1.

- First, when the example is fake (the left end of the figure), both the maximum likelihood game and the original minimax game suffer from the vanishing gradient problem. The heuristically motivated non-saturating game does not have this problem.
- Second, the maximum likelihood game also has the problem that almost all of the gradient occurs at the right end of the curve, which means that a rather small number of examples in each mini-batch dominate the gradient computation. This demonstrates that variance reduction methods based on the maximum likelihood game could be an important research direction for improving GAN performance.
- Third, the heuristically motivated non-saturating game has lower example variance, which is one possible reason why it is more successful in real applications.

GAN Lab [112] was proposed as an interactive visualization tool designed for non-experts to learn and experiment with GANs. Bau *et al.* [113] presented an analytic framework for visualizing and understanding GANs.

3.2 GAN Representative Variants

There are many papers related to GANs [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], such as least squares GAN (LSGAN) [23], cyclic-synthesized GAN (CSGAN) [127], and latent optimisation for GAN (LOGAN) [128]. In this subsection, we will introduce the representative GAN variants.

3.2.1 InfoGAN

Rather than utilizing a single unstructured noise vector z, decomposing the input noise vector into two parts was proposed for information maximizing GAN (InfoGAN) [17]: z, which is considered incompressible noise, and c, which is called the latent code and targets the significant structured semantic features of the real data distribution. InfoGAN [17] aims to solve

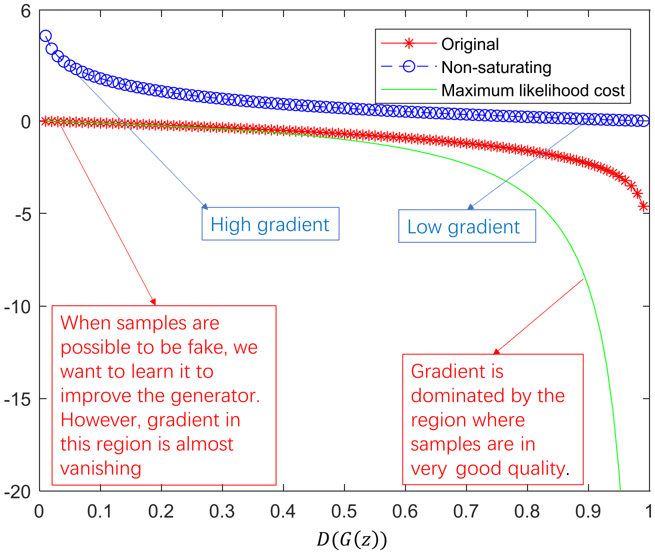

Fig. 1. The three curves for "Original", "Non-saturating", and "Maximum likelihood cost" denote $\log(1-D(G(z)))$, $-\log(D(G(z)))$, and $-D(G(z))/(1-D(G(z)))$ in (1), (7), and (13), respectively. The cost to the generator when generating an example $G(z)$ is determined only by the discriminator response to that generated example. The larger the probability that the discriminator gives the real label to the generated example, the smaller the cost that the generator bears. This figure is reproduced from [91], [111].

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I(c; G(z,c)), \tag{14}$$

where $V(D,G)$ is the objective function of the original GANs, $G(z,c)$ is the generated example, I is the mutual information, and λ is a tunable regularization parameter. Maximizing $I(c; G(z,c))$ maximizes the mutual information between c and $G(z,c)$, causing c to contain as many important and meaningful features of the real examples as possible. In practice, however, $I(c; G(z,c))$ is difficult to optimize directly since this requires access to the posterior $P(c|x)$. Fortunately, we can obtain a lower bound of $I(c; G(z,c))$ by defining an auxiliary distribution $Q(c|x)$ to approximate $P(c|x)$. The final objective function of InfoGAN [17] is

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda L_I(c; Q), \tag{15}$$

where $L_I(c;Q)$ is the lower bound of $I(c; G(z,c))$. InfoGAN has several variants, such as causal InfoGAN [129] and semi-supervised InfoGAN (ss-InfoGAN) [130].

3.2.2 Conditional GANs (cGANs)

GANs can be extended to a conditional model if both the discriminator and generator are conditioned on extra information y. The objective function of conditional GANs [18] is

$$\begin{aligned}\min_G \max_D V(D,G) = {} & E_{x\sim p_{data}(x)}[\log D(x|y)] \\ & + E_{z\sim p_z(z)}[\log(1-D(G(z|y)))].\end{aligned} \tag{16}$$

By comparing (15) and (16), we can see that the InfoGAN generator is similar to that of cGANs. However, the latent code c of InfoGAN is not known; it is discovered through training. Furthermore, InfoGAN has an additional network Q to output the conditional variables $Q(c|x)$.

Based on cGANs, we can generate examples conditioned on class labels [33], [131], text [37], [132], [133], bounding boxes and keypoints [134]. In [37], [135], text to photo-realistic image synthesis was conducted with stacked generative adversarial networks (SGAN) [136]. Various cGANs have also been used for convolutional face generation [137], face aging [138], image translation [139], outdoor image synthesis with specific scenery attributes [140], natural image description [141], and 3D-aware scene manipulation [142]. Chrysos *et al.* [143] proposed robust cGANs. Thekumparampil *et al.* [144] discussed the robustness of conditional GANs to noisy labels. Conditional CycleGAN [19] used cGANs with cyclic consistency. Mode seeking GANs (MSGANs) [145] were proposed with a simple yet effective regularization term to address the mode collapse issue for cGANs.

The discriminator of original GANs [6] is trained to maximize the log-likelihood that it has assigned an example to the correct source [33]:

$$\begin{aligned}L = {} & E[\log P(S = real|X_{real})] \\ & + E\big[\log\big(P\big(S = fake|X_{fake}\big)\big)\big],\end{aligned} \tag{17}$$

which is equivalent to (1). In contrast, the objective function of the auxiliary classifier GAN (AC-GAN) [33], [146] has two parts: the log-likelihood of the correct source, L_S, and the log-likelihood of the correct class label, L_C. Note that L_S is equivalent to L in (17). L_C is defined as following:

$$\begin{aligned}L_C = {} & E[\log P(C = c|X_{real})] \\ & + E\big[\log\big(P\big(C = c|X_{fake}\big)\big)\big].\end{aligned} \tag{18}$$

The discriminator and generator of AC-GAN maximize $L_C + L_S$ and $L_C - L_S$, respectively. AC-GAN was the first GAN variant that was able to produce recognizable examples of all ImageNet [147] classes.

The discriminators of most cGANs-based methods [34], [44], [148], [149], [150] add conditional information y into the discriminator by simply concatenating (embedded) y with the input or with the feature vector in some middle layer. cGANs with a projection discriminator [151] adopt an inner product between the condition vector y and the feature vector.

Isola *et al.* [152] used cGANs and sparse regularization for image-to-image translation. The corresponding software is called pix2pix. In GANs, the generator learns a mapping from random noise z to $G(z)$. In contrast, no noise is input to the generator of pix2pix. One novel aspect of pix2pix is that its generator learns a mapping from an observed image y and outputs image $G(y)$, for example, from a grayscale image to a color image. In [152], the objective of cGANs is expressed as following:

$$\begin{aligned}L_{cGANs}(D,G) = {} & E_{x,y}[\log D(x,y)] \\ & + E_y[\log(1-D(y,G(y)))].\end{aligned} \tag{19}$$

Furthermore, the l_1 distance is used

$$L_{l_1}(G) = E_{x,y}\big[\|x - G(y)\|_1\big]. \tag{20}$$

The final objective of [152] is

$$L_{cGANs}(D,G)+\lambda L_{l_1}(G), \tag{21}$$

where λ is the free parameter.

As a follow-up to pix2pix, pix2pixHD [153] used cGANs and feature matching loss for high-resolution image synthesis and semantic manipulation. For the discriminators, the learning problem is a multi-task learning problem:

$$\min_G \max_{D_1,D_2,D_3} \sum_{k=1,2,3} L_{GAN}(G,D_k). \tag{22}$$

The training set consists of pairs of corresponding images $\{(s_i,x_i)\}$, where x_i is a natural photo and s_i is a corresponding semantic label map. The ith-layer feature extractor of discriminator D_k is denoted as $D_k^{(i)}$ (from the input to the ith layer of D_k). The feature matching loss $L_{FM}(G,D_k)$ is

$$L_{FM}(G,D_k)=E_{(s,x)}\sum_{i=1}^{T}\frac{1}{N_i}\left[\left\|D_k^{(i)}(s,x)-D_k^{(i)}(s,G(s))\right\|_1\right], \tag{23}$$

where N_i is the number of elements in each layer and T denotes the total number of layers. The final objective function of [153] is

$$\min_G \max_{D_1,D_2,D_3} \sum_{k=1,2,3} (L_{GAN}(G,D_k)+\lambda L_{FM}(G,D_k)). \tag{24}$$

3.2.3 CycleGAN

Image-to-image translation is a class of graphics and vision problems in which the goal is to learn a mapping between an input image and an output image using a training set of aligned image pairs. When paired training data are available, reference [152] can be used for such image-to-image translation tasks. However, reference [152] cannot be used for unpaired data (when no input/output pairs are available); instead, this problem was well solved by cycle-consistent GANs (CycleGAN) [154]. CycleGAN is an important model for unpaired data. The cycle consistency was proven to be an upper bound of the conditional entropy [155]. CycleGAN is derived as a special case within the proposed variational inference (VI) framework [156], which naturally establishes its relationship with approximate Bayesian inference methods.

The basic ideas of learning to discover cross-domain relations with GANs (DiscoGAN) [157] and CycleGAN [154] are nearly the same. Both models were proposed separately at nearly the same time. The only difference between CycleGAN [154] and DualGAN [158] is that DualGAN uses the loss format advocated by the Wasserstein GAN (WGAN) rather than the sigmoid cross-entropy loss used in CycleGAN.

3.2.4 Summary

The website "The GAN Zoo" (https://github.com/hindupuravinash/the-gan-zoo) lists many GAN variants. Please refer to this website for more details.

3.3 GAN Training

Despite the theoretical existence of unique solutions, GAN training is difficult and often unstable for several reasons [32], [35], [159]. One difficulty stems from the fact that the optimal weights for GANs correspond to saddle points rather than minima of the loss function.

Many papers exist that focus on GAN training. Yadav *et al.* [160] stabilized GAN training using prediction methods. By using independent learning rates, [161] proposed a two time-scale update rule (TTUR) for both the discriminator and generator to ensure that the model would converge to a stable local Nash equilibrium. Arjovsky [159] took theoretical steps toward fully understanding the training dynamics of GANs; analyzed why GANs are difficult to train; studied and proved several problems including saturation and instability, that can occur when training GANs; examined a practical and theoretically grounded direction to mitigate these problems; and introduced new tools to study them.

One approach to improving GAN training is to assess the empirical "symptoms" that might occur in training. These symptoms include mode collapse (*cf.* Subsection 4.2); the discriminator loss converging quickly to zero [159] and providing no gradient updates to the generator; and difficulties in making both the generator and discriminator converge [35].

Here, we introduce GAN training from three perspectives: objective function, skills, and structure.

3.3.1 Objective Function

As discussed in Subsection 3.1, utilizing the original objective function in Eq. (1) can cause the vanishing gradient problem when training G, while utilizing the alternative G loss (12) in the non-saturating game can result in the mode collapse problem. These problems are directly caused by the objective function and cannot be solved by changing the GAN structure. Re-designing the objective function is a natural solution to mitigate these problems. Based on the theoretical flaws of GANs, many objective function based variants have been proposed that change the objective function of GANs based on theoretical analyses, such as least squares generative adversarial networks [24], [25]. Lucic *et al.* [162] conducted a large-scale experimental study and found that no GAN variant consistently outperformed the original GANs. Next, we introduce a series of objective function based variants.

3.3.1.1 Least squares generative adversarial networks (LSGANs): LSGANs [24], [25] were proposed to overcome the vanishing gradient problem in the original GANs. The decision boundary for D of original GANs was shown to provide only very small penalties to update G when generated examples are far from the decision boundary. Thus, LSGANs adopt least squares loss rather than the cross-entropy loss used in the original GANs. Suppose that a-b coding is used for the LSGANs discriminator [24], where a and b are the labels for the generated and real examples, respectively. The LSGANs discriminator loss $V_{LSGAN}(D)$ and generator loss $V_{LSGAN}(G)$ are defined as follows:

$$\begin{aligned}\min_D V_{LSGAN}(D)=&E_{x\sim p_{data}(x)}\left[(D(x)-b)^2\right]\\&+E_{z\sim p_z(z)}\left[(D(G(z))-a)^2\right],\end{aligned} \tag{25}$$

$$\min_G V_{LSGAN}(G) = E_{z\sim p_z(z)}\Big[(D(G(z)) - c)^2\Big], \tag{26}$$

where c is the value that G hopes for D to believe for generated examples. The authors of [24] showed that LSGANs have two advantages over the original GANs.

- The new decision boundary produced by D imposes a large penalty for generated examples that are far from the decision boundary, which forces the "low quality" generated examples to move toward the decision boundary. This approach is effective at generating higher quality examples.
- Penalizing generated examples far from the decision boundary results in larger gradients when updating G, which overcomes the vanishing gradient problems in the original GANs.

3.3.1.2 f-GAN: The KL divergence measures the difference between two probability distributions. A large class of assorted divergences are the so-called Ali-Silvey distances, also known as the f-divergences [163]. Given two probability distributions P and Q that have absolutely continuous density functions p and q, respectively, with regard to a base measure dx defined on domain X, the f-divergence is defined as following:

$$D_f(P\|Q) = \int_X q(x) f\left(\frac{p(x)}{q(x)}\right) dx. \tag{27}$$

Different choices of f recover popular divergences as special cases of the f-divergence. For example, if $f(a) = a\log a$, the f-divergence becomes the KL divergence. The original GANs [6] are a special case of f-GAN [20], which is based on the f-divergence. The authors of [20] showed that any f-divergence can be used for training GANs. Furthermore, [20] discussed the advantages of different choices of divergence functions on both the quality of the produced generative models and the training complexity. Im *et al.* [164] quantitatively evaluated GANs with divergences proposed for training. Uehara *et al.* [165] further extended f-GAN by directly minimizing the f-divergence in the generator step; then, the ratio of the real and generated data distributions are predicted in the discriminator step.

3.3.1.3 Integral probability metrics (IPMs): $\mathcal{P}$ denotes the set of all Borel probability measures on a topological space $(M, \mathcal{A})$. The integral probability metric (IPM) [166], [167] between two probability distributions $P \in \mathcal{P}$ and $Q \in \mathcal{P}$ is defined as

$$\gamma_{\mathcal{F}}(P, Q) = \sup_{f\in\mathcal{F}}\left|\int_M f dP - \int_M f dQ\right|, \tag{28}$$

where $\mathcal{F}$ is a class of real-valued bounded measurable functions on M. IPMs include the reproducing kernel Hilbert space (RKHS)-induced maximum mean discrepancy (MMD) [168] and the Wasserstein distance used in WGAN.

MMD: The following definition of the MMD can be found in [169]. Here, $\mathcal{X}$ represents the input domain, which is assumed to be a nonempty compact set.

Definition 1. *Let $\mathcal{E}$ be a class of functions $f : \mathcal{E} \to R$. Let P and Q be Borel probability distributions, and let $X = (x_1, \cdots, x_m)$ and $Y = (y_1, \cdots, y_n)$ be examples consisting of independent and identically distributed observations drawn from P and Q, respectively. Then, the MMD and its empirical estimate are defined as follows:*

$$MMD(\mathcal{E}, P, Q) = \sup_{f\in\mathcal{E}}\big(E_{x\sim P}[f(x)] - E_{y\sim Q}[f(y)]\big) MMD(\mathcal{E}, X, Y) = \sup_{f\in\mathcal{E}}\left(\frac{1}{m}\sum_{i=1}^{m} f(x_i) - \frac{1}{n}\sum_{i=1}^{n} f(y_i)\right). \tag{29}$$

When $\mathcal{E}$ is the unit ball in a universal RKHS, Theorem 2.2 in [169] guarantees that $MMD(\mathcal{E}, P, Q)$ will detect any discrepancy between P and Q. The MMD has been widely used for GANs [170], [171], [172], [173], [174], [175], [176], [177].

WGAN: The authors of [21] conducted a comprehensive theoretical analysis of how the Wasserstein-1 distance behaves in comparison with popular probability distances and divergences such as the total variation (TV) distance, the KL divergence, and the JS divergence utilized in the context of learning distributions. The definition of the Wasserstein-1 distance is

$$W(p_{data}, p_g) = \inf_{\gamma\in\Pi\left(p_{data}, p_g\right)} E_{(x,y)\in\gamma}[\|x - y\|], \tag{30}$$

where $\Pi\left(p_{data}, p_g\right)$ denotes the set of all joint distributions $\gamma(x, y)$ whose marginals are p_{data} and p_g. However, the infimum in (30) is highly intractable. According to the Kantorovich-Rubinstein duality [178], we know that

$$W(p_{data}, p_g) = \sup_{\|f\|_L\le 1} E_{x\in p_{data}}[f(x)] - E_{x\in p_g}[f(x)] \tag{31}$$

where the supremum is taken over all the 1-Lipschitz functions f. In [21], $\|f\|_L \le 1$ was replaced with $\|f\|_L \le K$ (considering K-Lipschitz for some constant K), and $K \cdot W(p_{data}, p_g)$ was obtained. The authors of [21] used the following equation to approximate the Wasserstein-1 distance:

$$\max_{w\in\mathcal{W}} E_{x\sim p_{data}(x)}[f_w(x)] - E_{z\sim p_z(z)}[f_w(G(z))], \tag{32}$$

where a parameterized family of functions $\{f_w\}_{w\in\mathcal{W}}$ exists that are all K-Lipschitz for some K, and f_w can be realized by the discriminator D. When D is optimized, (32) denotes the approximated Wasserstein-1 distance. Then, the aim of G is to minimize (32) to make the generated distribution as close to the real distribution as possible. Therefore, the overall objective function of WGAN is

$$\begin{aligned}\min_G\ &\max\nolimits_{w\in\mathcal{W}} E_{x\sim p_{data}(x)}[f_w(x)] - E_{z\sim p_z(z)}[f_w(G(z))]\\ &= \min_G \max_D E_{x\sim p_{data}(x)}[D(x)] - E_{z\sim p_z(z)}[D(G(z))].\end{aligned} \tag{33}$$

By comparing (1) and (33), we can see three differences between the objective function of the original GANs and that of the WGAN:

- First, there is no *log* in the objective function of WGAN.

- Second, the D in the original GANs is utilized as a binary classifier, while the D in WGAN is utilized to approximate the Wasserstein distance, which is a regression task. Therefore, the sigmoid function that appears in the last layer of D is not used in WGAN; the discriminator of the original GANs outputs a value between zero and one, while no such constraint exists for WGAN.
- Third, the D in WGAN is required to be K-Lipschitz for some K; therefore, WGAN uses weight clipping.

Compared with traditional GAN training, WGAN improves the learning stability and provides meaningful learning curves that are useful for hyperparameter searches and debugging. However, approximating the K-Lipschitz constraint is challenging, which is required by the Wasserstein-1 metric. WGAN-GP, proposed in [22], uses a gradient penalty to restrict the K-Lipschitz constraint, and the WGAN-GP objective function is

$$\begin{aligned} L = &-E_{x\sim p_{data}}[D(x)] + E_{\tilde{x}\sim p_g}[D(\tilde{x})] \\ &+\lambda E_{\hat{x}\sim p_{\hat{x}}}\left[\left(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1\right)^2\right] \end{aligned} \tag{34}$$

where the first two terms are the WGAN objective function and $\hat{x}$ is sampled from the distribution $p_{\hat{x}}$; these are uniform examples along straight lines between pairs of points sampled from the real data distribution p_{data} and the generated distribution p_g. Gradient penalties are now a commonly used approach in GANs, following [179], [180], [181]. Some other methods are closely related to WGAN-GP, such as deep regret analytic GAN (DRAGAN) [182]. Wu *et al.* [183] proposed a novel and relaxed version of the Wasserstein-1 metric called the Wasserstein divergence (W-div), which does not require the K-Lipschitz constraint. Based on W-div, Wu *et al.* [183] introduced a Wasserstein divergence objective for GANs (WGAN-div) that faithfully approximates W-div through optimization. The Wasserstein distance was argued to lead to biased gradients, and the use of the Cramér distance between two distributions was suggested and implemented in CramerGAN [184]. Other papers related to WGAN can be found in [185], [186], [187], [188], [189].

3.3.1.4: Spectrally normalized GANs (SN-GANs): A novel weight normalization method named spectral normalization to stabilize the discriminator training was proposed in SN-GANs [26]. This new normalization technique is both computationally efficient and easy to integrate into existing methods. Spectral normalization [26] uses a simple method to make the weight matrix W satisfy the Lipschitz constraint $\sigma(W) = 1$:

$$\bar{W}_{SN}(W) := W/\sigma(W), \tag{35}$$

where W is the weight matrix of each layer in D, and $\sigma(W)$ is the spectral norm of W. As shown in [26], SN-GANs can generate images of equal or better quality than the previous training stabilization methods. In theory, spectral normalization can be applied to all GAN variants. Both BigGANs [39] and self-attention GAN (SAGAN) [38] use spectral normalization and have achieved good performances on ImageNet.

3.3.1.5 Relativistic GANs (RGANs): In the original GANs, the discriminator can be defined according to the non-transformed layer $C(x)$ as $D(x) = \sigma(C(x))$. A simple way to make the discriminator relativistic (i.e., to make the output of D depend on both real and generated examples) [31] is to sample from real and generated data pairs $\tilde{x} = (x_r, x_g)$, which is defined as

$$D(\tilde{x}) = \sigma\big(C(x_r) - C(x_g)\big). \tag{36}$$

This modification can be interpreted in the following way [31]: D estimates the probability that the given real example is more realistic than a randomly sampled generated example. Similarly, $D_{rev}(\tilde{x}) = \sigma\big(C(x_g) - C(x_r)\big)$ can be interpreted as the probability that the given generated example is more realistic than a randomly sampled real example. The discriminator and generator loss functions of the relativistic standard GAN (RSGAN) are

$$L_D^{RSGAN} = -E_{(x_r,x_g)}\left[\log\left(\sigma\big(C(x_r) - C(x_g)\big)\right)\right], \tag{37}$$

$$L_G^{RSGAN} = -E_{(x_r,x_g)}\left[\log\left(\sigma\big(C(x_g) - C(x_r)\big)\right)\right]. \tag{38}$$

Most GANs can be parameterized

$$L_D^{GAN} = E_{x_r}[f_1(C(x_r))] + E_{x_g}\left[f_2\big(C(x_g)\big)\right], \tag{39}$$

$$L_G^{GAN} = E_{x_r}[g_1(C(x_r))] + E_{x_g}\left[g_2\big(C(x_g)\big)\right], \tag{40}$$

where f_1, f_2, g_1, and g_2 are scalar-to-scalar functions. If we adopt a relativistic discriminator, the loss functions of these GANs become

$$\begin{aligned} L_D^{RGAN} = &E_{(x_r,x_g)}\left[f_1\big(C(x_r) - C(x_g)\big)\right] \\ &+ E_{(x_r,x_g)}\left[f_2\big(C(x_g) - C(x_r)\big)\right] \end{aligned}, \tag{41}$$

$$\begin{aligned} L_G^{RGAN} = &E_{(x_r,x_g)}\left[g_1\big(C(x_r) - C(x_g)\big)\right] \\ &+ E_{(x_r,x_g)}\left[g_2\big(C(x_g) - C(x_r)\big)\right]. \end{aligned} \tag{42}$$

3.3.2 Skills

NIPS 2016 held a workshop on adversarial training and invited Soumith Chintala to give a talk called "How to train a GAN". This talk included assorted tips and tricks, such as suggesting that when labels are available, also training the discriminator to classify the examples is useful, as in AC-GAN [33]. Readers can refer to the GitHub repository associated with Soumith's talk, https://github.com/soumith/ganhacks, for more advice.

Salimans *et al.* [32] proposed useful and improved techniques for training GANs (ImprovedGANs), such as feature matching, mini-batch discrimination, historical averaging, one-sided label smoothing, and virtual batch normalization.

3.3.3 Structure

The original GANs utilized multi-layer perceptrons (MLPs). Specific types of structures may be better for specific applications, e.g., recurrent neural networks (RNNs) for time series data and convolutional neural networks (CNNs) for images.

3.3.3.1 The original GANs: The original GANs used MLPs for both the generator G and discriminator D.

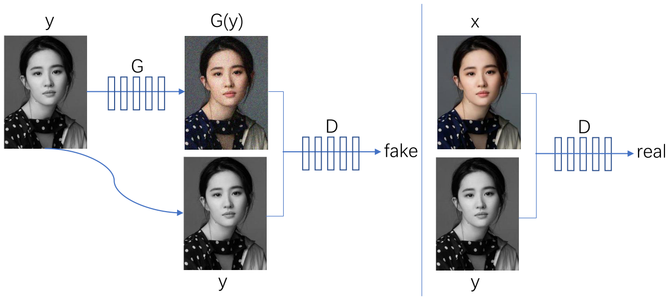

Fig. 2. pix2pix: training conditional GANs to map grayscale images → color images. The discriminator D learns to classify between real {grayscale, color} and fake (synthesized by the generator) tuples. The generator G learns to fool the discriminator. Different from the original GANs, both the generator and discriminator receive the grayscale image as input, and the pix2pix generator receives no noise input.

However, an MLP can be used only for small datasets such as CIFAR-10 [190], MNIST [191], and the Toronto Face Database (TFD) [192]; it does not generalize well to more complex images [14].

3.3.3.2 Deep convolutional generative adversarial networks (DCGANs): In the original GANs, G and D are defined using an MLP. Because CNNs are better at images than MLPs, G and D are defined by deep convolutional neural networks (DCNNs) in DCGANs [35], which have better performance. Most current GANs are at least loosely based on the DCGAN architecture [35]. The three key features of the DCGAN architecture are listed as follows.

- First, the overall architecture is based largely on an all-convolutional net [193], which includes neither pooling nor "unpooling" layers. When G needs to increase the spatial dimensionality of the representation, it uses transposed convolution (deconvolution) with a stride greater than 1.
- Second, DCGANs use batch normalization for most of the layers of both G and D. The last layer of G and first layer of D are not batch normalized, which allows the neural network to learn the correct mean and scale of the data distribution.
- Third, DCGANs use the adaptive moment estimation (Adam) optimizer instead of stochastic gradient descent (SGD) with momentum.

3.3.3.3 Progressive GAN: A new training methodology for GANs was proposed and implemented in progressive GAN (PGGAN) [36]. The structure of PGAN is based on progressive neural networks, which were first proposed in [194]. The key idea of PGAN is to train both the generator and discriminator progressively: starting at a low resolution and adding new layers that model increasingly fine details as training progresses.

3.3.3.4 Self-Attention Generative Adversarial Network (SAGAN): SAGAN [38] was proposed to allow attention-driven, long-range dependency modeling for image generation tasks. The spectral normalization technique had previously been applied only to the discriminator [26], but SAGAN uses spectral normalization for both the generator and discriminator, which improves the training dynamics. Furthermore, SAGAN confirmed that TTUR [161] was effective.

Note that AttnGAN [195] utilizes attention over word embeddings within an input sequence rather than self-attention over internal model states.

3.4 Summary

As discussed, many GAN variants have been constructed; some of the milestone variants are shown in Fig. 3. Note that due to space limitations, only a limited number of variants are shown.

The objective function based variants of GANs can be generalized to structure variants. Compared with other objective function based variants, both SN-GANs and RGANs show stronger generalization ability. These two objective function based variants can be generalized to the other objective function based variants. Spectral normalization can be generalized to any type of GAN variant, while RGANs can be generalized to any IPM-based GANs.

Objective function based variants such as energy-based generative adversarial network (EBGAN) [41] and boundary equilibrium generative adversarial networks (BEGAN) [42], structure variants such as Laplacian generative adversarial networks (LAPGAN) [34] and SinGAN [196], evaluation metrics for GANs, and task-driven GANs are discussed in the supplementary material, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TKDE.2021.3130191.

4 Theory

In this section, we first introduce maximum likelihood estimation. Then, we introduce mode collapse. Finally, we discuss other theoretical issues, such as memorization.

4.1 Maximum Likelihood Estimation (MLE)

Not all generative models use MLE. Some generative models do not utilize MLE but can be made to do so (GANs belong to this category). Minimizing the KL divergence between $p_{data}(x)$ and $p_g(x)$ can be simply proven to be

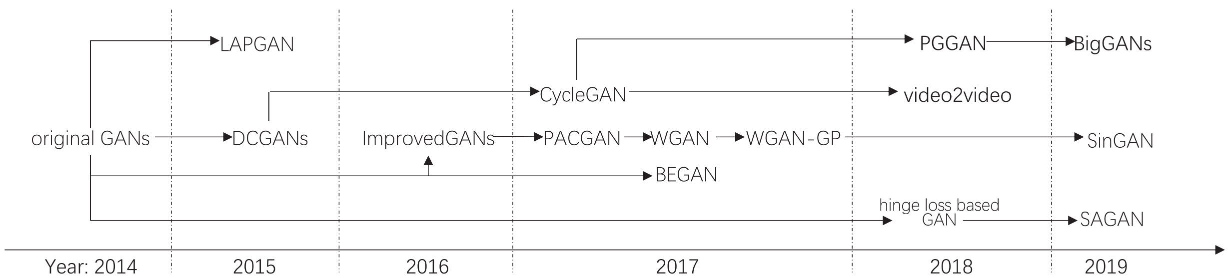

Fig. 3. Road map of GANs showing milestone variants.

equivalent to maximizing the log-likelihood as the number of examples m increases:

$$\begin{aligned}\theta^* &= \arg\min_{\theta}\ KLD(p_{data}\|p_g)\\ &= \arg\min_{\theta}\ -\int p_{data}(x)\log\frac{p_g(x)}{p_{data}(x)}dx\\ &= \arg\min_{\theta}\int p_{data}(x)\log p_{data}(x)dx\\ &\quad -\int p_{data}(x)\log p_g(x)dx\\ &= \arg\max_{\theta}\int p_{data}(x)\log p_g(x)dx\\ &= \arg\max_{\theta}\ \lim_{m\to\infty}\frac{1}{m}\sum\nolimits_{i=1}^{m}\log p_g(x_i).\end{aligned} \tag{43}$$

The model probability distribution $p_\theta(x)$ is replaced with $p_g(x)$ for notation consistency. Refer to Chapter 5 of [197] for more information on MLE and other statistical estimators.

4.2 Mode Collapse

GANs are notoriously difficult to train, and they have been observed [29], [32] to suffer from mode collapse [198], [199], in which the generator learns to generate examples from only a few modes of the data distribution and misses many other modes, even if examples of the missing modes exist throughout the training data. In the worst case, the generator simply produces a single example (complete collapse) [159], [200]. In this subsection, we first introduce two viewpoints regarding GAN mode collapse. Then, we introduce methods that propose new objective functions or new structures to solve the mode collapse problem.

4.2.1 Two Viewpoints: Divergence and Algorithmic

We can resolve and understand GAN mode collapse and instability from both divergence and algorithmic viewpoints.

Divergence Viewpoint. Roth *et al.* [179] stabilized the training of GANs and their variants, such as f-divergence based GANs (f-GAN), through regularization.

Algorithmic Viewpoint. The numerics of common algorithms for training GANs were analyzed and a new algorithm with better convergence was proposed in [201]. Mescheder *et al.* [180] showed which training methods for GANs actually converge.

4.2.2 Methods to Overcome Mode Collapse

Objective Function Based Methods. Mode collapse was suggested to occur because of a fake local Nash equilibrium in the non-convex problem [182]. DRAGAN solved this problem by constraining the gradients of the discriminator around the real data manifold. It added a gradient penalizing term that biases the discriminator to have a gradient norm of 1 around the real data manifold. Other methods, such as LSGANs and SN-GANs (detailed in Section 3.3), also belong to this category.

Structure-Based Methods. The representative methods in this category include DCGANs and SAGAN (detailed in Section 3.3).

Other methods also exist that can reduce mode collapse in GANs. For example, PACGAN [202] alleviated mode collapse by changing the input to the discriminator.

4.3 Other Theoretical Issues

4.3.1 Do GANs Actually Learn the Distribution?

Perhaps the most crucial aspect of GAN theory is whether the distributions are modeled. Both true data distributions and GAN generator distributions have their own densities. As [159] noted, neither distribution typically has a density in GANs. Furthermore, [159] studied and proved the problems involved in training GANs, such as saturation and instability, investigated directions to mitigate these problems and introduced new tools to study them.

Several studies [44], [200], [203] both empirically and theoretically shed light on the fact that distributions learned by GANs suffer from mode collapse. In contrast, Bai *et al.* [204] showed that GANs can in principle learn distributions using the Wasserstein distance (or KL divergence in many situations) with polynomial sample complexity if the discriminator class has strong discriminating power against the particular generator class (instead of against all possible generators). Liang *et al.* [205] studied how well GANs learn densities, including nonparametric and parametric target distributions. Singh *et al.* [206] further studied nonparametric density estimation with adversarial losses.

4.3.2 Divergence/Distance

Arora *et al.* [200] showed that GAN training may not result in good generalization properties (e.g., training may look successful, but the generated distribution may be far from the real data distribution using standard metrics). Popular distances such as Wasserstein and JS may not generalize well. However, generalization can still occur by introducing a novel notion of distance between distributions—the neural net distance—which raises the issue of whether other useful divergences exist.

4.3.3 Mathematical Perspectives Such as Optimization

Mohamed *et al.* [207] used their understanding of GANs to build connections to the diverse set of statistical thinking regarding GANs. Gidel *et al.* [208] examined optimization approaches designed for GANs and cast GAN optimization problems into the general variational inequality framework. The convergence and robustness of training GANs with regularized optimal transport are discussed in [209].

4.3.4 Memorization

Regarding "memorization of GANs", Nagarajan *et al.* [210] argued that making the generator "learn to memorize" the training data is more difficult than making it "learn to output realistic but unseen data".

5 Applications

As discussed earlier, GANs are powerful generative models that can generate realistic-looking examples with a random vector z. GANs neither need to know an explicit true data distribution nor require any prior mathematical assumptions. These advantages allow GANs to be widely applied

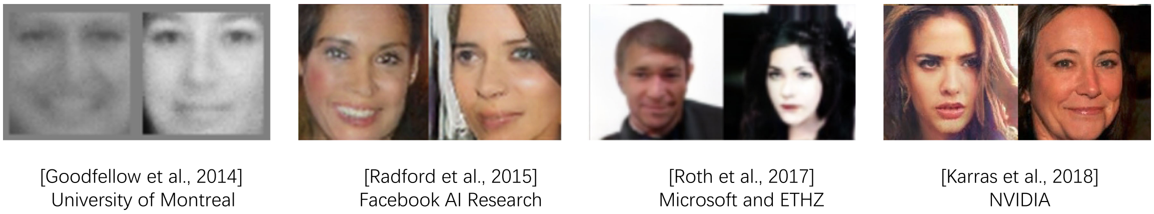

Fig. 4. Face image synthesis.

to many fields, such as image processing, computer vision, and sequential data.

5.1 Image Processing and Computer Vision

The most successful applications of GANs are in image processing and computer vision, such as image super-resolution, image synthesis and manipulation, and video processing.

5.1.1 Super-Resolution (SR)

SRGAN [51], which is a GAN model for performing SR, was the first framework able to infer photo-realistic natural images for 4× upscaling factors. To further improve the visual quality of SRGAN, Wang *et al.* [52] thoroughly studied three of its key components and improved each one to derive an enhanced SRGAN (ESRGAN). For example, ESRGAN uses the idea from relativistic GANs [31] of having the discriminator predict relative realness rather than absolute value. Benefiting from these improvements, ESRGAN won first place in the PIRM2018-SR Challenge (region 3) [211] and obtained the best perceptual index. Based on CycleGAN [154], cycle-in-cycle GANs [53] were proposed for unsupervised image SR. SRDGAN [54] were proposed to learn the noise prior for SR with DualGAN [158]. Deep tensor generative adversarial nets (TGAN) [55] were proposed to generate large high-quality images by exploring tensor structures. Specific methods have been designed for face SR [212], [213], [214]. Other related methods can be found in [215], [216], [217], [218].

5.1.2 Image Synthesis and Manipulation

5.1.2.1 Faces: *Pose related:* Disentangled representation learning GAN (DR-GAN) [219] was proposed for pose-invariant face recognition. Huang *et al.* [57] proposed a two-pathway GAN (TP-GAN) for photorealistic frontal view synthesis by simultaneously perceiving both local details and global structures. Ma *et al.* [58] proposed the novel pose guided person generation network (PG^2) that synthesizes person images in arbitrary poses based on a novel pose and an image of that person. Cao *et al.* [220] proposed a high-fidelity pose-invariant model for high-resolution face frontalization based on GANs. Siarohin *et al.* [221] proposed deformable GANs for pose-based human image generation. Pose-robust spatial-aware GAN (PSGAN) was proposed for customizable makeup transfer in [59].

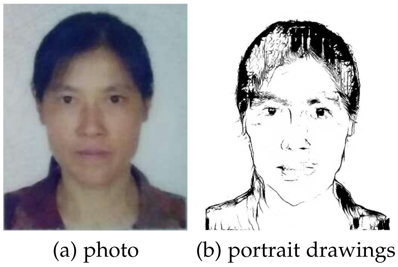

Fig. 5. Given a photo such as the image in (a), APDrawingGAN can produce corresponding artistic portrait drawings such as the image in (b).

Portrait Related: APDrawingGAN [60] was proposed to generate artistic portrait drawings from face photos with hierarchical GANs. APDrawingGAN has software based on WeChat, and the results are shown in Fig. 5. GANs have also been used in other face-related applications, such as facial attribute changes [222] and portrait editing [223], [224], [225], [226].

Face Generation: The quality of faces generated by GANs has steadily improved year over year; examples can be found in Sebastian Nowozin's GAN lecture materials[1]. As shown in Fig. 4, faces generated based on the original GANs [6] have poor visual qualities and serve only as a proof of concept. Radford *et al.* [35] used better neural network architectures—deep convolutional neural networks—for generating faces. Roth *et al.* [179] addressed GAN training instability problems, which allowed larger architectures such as ResNet to be utilized. Karras *et al.* [36] utilized multi-scale training to enable megapixel face image generation with high fidelity.

Face generation [19], [227], [228], [229], [230], [231], [232], [233] is relatively easy because the problem includes only one class of objects. Every object is a face, and most face datasets tend to be composed of people looking straight into the camera. Most people are registered by putting nose, eyes, and other landmarks in consistent locations.

5.1.2.2 General objects: Having GANs work on assorted data sets, such as ImageNet [147], which has a thousand different object classes, is slightly more difficult. However, progress on this task has been rapid in recent years, and the quality of such generated images has steadily improved [180].

Most studies use GANs to synthesize 2D images [234], [235]; however, Wu *et al.* [236] synthesized three-dimensional (3D) novel objects such as cars, chairs, sofas, and tables using GANs and volumetric convolutions. Im *et al.* [237] generated images with recurrent adversarial networks. Yang *et al.* [238] proposed layered recursive GANs (LR-GAN) for image generation.

5.1.2.3 Interaction between a human being and an image generation process: Many applications involve interactions

1. https://github.com/nowozin/mlss2018-madrid-gan

between a human being and an image generation process; however, realistic image manipulation in such situations is difficult because it requires allowing the user to control image modifications while still making them appear realistic. When the user does not have sufficient artistic skill, the image easily deviates from the manifold of natural images while editing. Interactive GAN (IGAN) [61] defines a class of image editing operations and constrains their output to lie on a learned manifold at all times. Introspective adversarial networks [62] also offer the ability to perform interactive photo editing; their results have been demonstrated mostly for face editing. GauGAN [63] can turn doodles into stunning, photorealistic landscapes.

5.1.3 Texture Synthesis

Texture synthesis is a classical problem in the image field. Markovian GANs (MGAN) [64] is a texture synthesis method based on GANs. By capturing the texture data of Markovian patches, MGAN can generate stylized videos and images very quickly and realize real-time texture synthesis. Spatial GAN (SGAN) [65] was the first to apply GANs with fully unsupervised learning to texture synthesis. Periodic spatial GAN (PSGAN) [66] is an SGAN variant that can learn periodic textures from either a single image or a large complex dataset.

5.1.4 Object Detection

How can we learn an object detector that is invariant to deformations and occlusions? One way is to use a data-driven strategy—collecting large-scale datasets that have numerous object examples that appear in different conditions. Using this strategy, we can simply hope that the final classifier can use these numerous instances to learn invariances. However, can all the possible deformations and occlusions be included in a dataset? Some deformations and occlusions are so rare that they almost never occur in real-world conditions; however, we want our method to be invariant to such situations. To address this problem, Wang *et al.* [239] used GANs to generate instances with deformations and occlusions. The goal of the generator is to generate instances that are difficult for the object detector to classify. By using a segmentation model and GANs, Segan [67] detected objects occluded by other objects in an image. To address the small object detection problem, Li *et al.* [68] proposed perceptual GANs, and Bai *et al.* [69] proposed an end-to-end multi-task GAN (MTGAN).

5.1.5 Video Applications

The first study to use GANs for video generation was [70]. Villegas *et al.* [240] proposed a deep neural network to predict future frames in natural video sequences using GANs. Denton and Birodkar [71] proposed a new model named disentangled representation net (DRNET) that learns disentangled image representations from a video based on GANs. A novel video-to-video synthesis approach (video2video) under a generative adversarial learning framework was proposed in [73]. MoCoGan [74] was proposed to decompose motion and content to generate videos [241], [242].

GANs have also been used in other video applications, such as video prediction [72], [243], [244] and video retargeting [245].

5.1.6 Other Image and Vision Applications

GANs have also been utilized in other image processing and computer vision tasks [246], [247], [248], such as object transfiguration [249], [250], semantic segmentation [251], visual saliency prediction [252], object tracking [253], [254], image dehazing [255], [256], [257], natural image matting [258], image inpainting [259], [260], image fusion [261], image completion [262], [263], and image classification [264].

Creswell *et al.* [265] showed that the representations learned by GANs can also be used for retrieval. GANs have also been used to anticipate where people will look next [266], [267].

5.2 Sequential Data

Additionally, GANs have made achievements in sequential data tasks, such as those involving natural language, music, speech, voice [268], [269], and time series data [270], [271], [272], [273].

Natural Language Processing (NLP). IRGAN [76], [77] was proposed for information retrieval (IR). Li *et al.* [274] used adversarial learning to generate neural dialogue. GANs have also been used for text generation [75], [275], [276], [277] and speech language processing [81]. KBGAN [278] was proposed to generate high-quality negative examples, and it was used in knowledge graph embeddings. Adversarial REward Learning (AREL) [279] was proposed for visual storytelling. DSGAN [280] was proposed for distant supervision relation extraction. ScratchGAN [281] was proposed to train a language GAN from scratch—without maximum likelihood pre-training.

Qiao *et al.* [78] learned text-to-image generation by redescription, and a text conditioned auxiliary classifier GAN (TAC-GAN) [282] was also proposed for text-to-image tasks. GANs have also been widely used for image-to-text tasks (image captioning) [283], [284].

Furthermore, GANs have been widely utilized in other NLP applications, such as question-answer selection [285], [286], poetry generation [287], talent-job fit [288], and review detection and generation [289], [290].

Music: GANs have also been used to generate music, including continuous RNN-GAN (C-RNN-GAN) [79], object-reinforced GAN (ORGAN) [80], and sequence GANs (SeqGAN) [81].

Speech and Audio. GANs have been used for speech and audio analysis, such as synthesis [291], [292], [293], enhancement [294], and recognition [295].

5.3 Other Applications

Medical Field. GANs have been widely utilized in the medical fields such as for generating and designing DNA [296], [297], drug discovery [298], generating multi-label discrete patient records [299], medical image processing [300], [301], [302], [303], [304], [305], [306], [307], and doctor recommendation [308].

Data Science. GANs have been used to generate data [309], [310], [311], [312], [313], [314], [315], [316], to generate neural networks [317], to augment data [318], [319], to learn spatial representations [320], and in network embedding [321], heterogeneous information networks [322], and mobile user profiling [323].

Finally, GANs have been widely applied to many other areas, such as malware detection [324], steganography [325], [326], [327], [328], privacy preserving [329], [330], [331], social robots [332], and network pruning [333], [334].

6 Conclusion

This paper provides a comprehensive review of various aspects of GANs by elaborating on several perspectives, i.e., algorithms, theory, and applications. We believe that this survey will help readers gain a thorough understanding of the existing research on GANs. To conclude, we would like to note that, in order to maintain an appropriate size of the article, we had to limit the number of referenced studies. We therefore apologize to the authors of papers that were not cited.

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