Since the concept of generative adversarial networks (GANs) was proposed in 2014, a large number of relevant researches have been made, such as diverse GANs' variants with corresponding improvements, training tricks with higher and stable training performance, evaluation metrics with the aim of reflecting the quality of the model reasonably, and a wide range of applications in various areas.

Various derived GANs models have emerged since 2014, and these derived GANs models can be roughly classified into two groups, architectures optimization based GANs and objective function optimization based GANs [1]. Some representative models are briefly introduced below, and they have their own advance compared to the original model and weaknesses as well.

A. Architecture optimization based GANs
   1. Convolution based GANs: In terms of the network structure of generator and discriminator, the original GANs adopt the Multi-Layer Perceptron (MLP) to make it work. However, CNN performs better than MLP in extracting image features, which is why deep convolutional generative adversarial networks (DCGANs) is proposed [2].
   2. Condition based GANs: If both the D and G are conditioned on some extra information c (can be labels, text or other data) to affect the data generation process, conditional GANs (CGANs) is proposed [3]. In addition, [4] proposed InfoGANs, which decompose the input vector into two parts. Although the generators of them are similar, but the latent information of the latter method is unknown [1],[5].
   3. Autoencoder based GANs: There are many tries to combine the idea of adversarial networks with autoencoder, such as Adversarial Autoencoder (AAE) [6], Adversarial Generator-Encoder Network (AGE) [7], Bidirectional GANs (BiGANs) [8], Adversarially Learned Inference (ALI) [9], etc.

B. Objective function optimization based GANs
   In the original GANs paper, two different objective functions for the generator are presented, but they have some problems – the "minimax" loss function will suffer from gradient vanishing and the "non-saturating" loss will encounter the mode collapse problem [5].
   1. Least squares GANs (LSGANs), which adopt the least squares loss rather than the cross-entropy loss in the original work for both the discriminator and the generator, are proposed to overcome the vanishing gradient problem [10],[11]. The method is able to generate higher quality images than regular GANs and performs more stably during the learning process.
   2. Energy-based GANs (EBGAN) is seen as an energy function, giving high energy to the fake ("generative") samples and lower energy to the real samples [12].
   3. Che rt al. [13] argue that GANs' unstable training and model collapse is due to the very special functional shape of the trained discriminators in high dimensional spaces, therefore Mode regularized GANs (MDGAN) is proposed to deal with these problems [5].

Besides, some tricks are suggested for achieving excellent training performance. As we know, Nash equilibrium is the goal of GANs training, but this is very difficult to implement the process. In [14], Salimans et al. propose several tricks which can improve the performance and stabilize the training process, for example firstly feature matching can make GANs training more stable by giving the generator a new objective function, secondly using the minibatch layer allows the discriminator to reflect the diversity of the sample to avoid the problem of mode collapse. In addition, [15] also advise a two time-scale update rule (TTUR) for both generator and discriminator to guarantee that the model can converge to a stable local Nash equilibrium by using separate learning rates.

However, evaluation metrics which are approved by most of researchers still does not come into an agreement, i.e. there is still no universal quantitative evaluation metrics [1]. There are four widely used evaluation metrics – Inception scores (IS), mode score (MS), fréche inception distance (FID), multi-scale structural similarity for image quality (MS-SSIM) – although they perform well in some aspect, they still have limitations. If the generative model falls into mode collapse, the IS might be still pretty when the real situation is bad [1]. The MS is an improved version of the IS, which can reflect the variety and visual quality of the generated samples at the same time, but it is not sensitive to prior distribution over the ground truth labels [16]. The FID can be used to detect the intra-class mode dropping, whereas the IS and FID cannot well handle the overfitting problem [1], [17]. The MS-SSIM is proposed for multi-scale image quality assessment, but [18] suggests that it should only be taken into account together with the FID and IS metrics for testing sample diversity. On the whole, it is still a hard problem to select an appropriate evaluation, which should distinguish generated samples from real one, verify mode collapse, mode drop and detect overfitting [1].

There are many fields where GANs has been applied. So far, the most successful applications of GANs are in the computer vision areas [5], including image super-resolution, image translation, image synthesis, video generation, etc. In addition, GANs also has some achievements in the field of language and speed processing, for instance SeqGAN based on the policy gradient outperforms traditional methods in terms of speech, poetry and music generation [19], RankGAN can generate sentences [20]. Besides, GANs is also applied in other domains, such as medicine, security, etc.

From my own perspective, finding a better evaluation metric is the topic most interesting to me. In terms of improving GANs' performance, there has been a majority of novel solutions, but in terms of the evaluation metrics of GANs there is still no a well-behaved and unified metric approved by most of researchers, though there have been some tries. Finding a better evaluation metric is of great importance, which could quantitatively evaluate a model and thus benefits to guide the research of GANs in the future.

Reference:

[1] Pan, Zhaoqing, Weijie Yu, Xiaokai Yi, Asifullah Khan, Feng Yuan, and Yuhui Zheng. "Recent progress on generative adversarial networks (GANs): A survey." *IEEE Access* 7 (2019): 36322-36333.

[2] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).

[3] Mirza, Mehdi, and Simon Osindero. "Conditional generative adversarial nets." *arXiv preprint arXiv:1411.1784* (2014).

[4] Chen, Xi, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, and Pieter Abbeel. "Infogan: Interpretable representation learning by information maximizing generative adversarial nets." In *Advances in neural information processing systems*, pp. 2172-2180. 2016.

[5] Gui, Jie, Zhenan Sun, Yonggang Wen, Dacheng Tao, and Jieping Ye. "A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications." *arXiv preprint arXiv:2001.06937* (2020).

[6] Makhzani, Alireza, Jonathon Shlens, Navdeep Jaitly, Ian Goodfellow, and Brendan Frey. "Adversarial autoencoders." *arXiv preprint arXiv:1511.05644* (2015).

[7] Ulyanov, Dmitry, Andrea Vedaldi, and Victor Lempitsky. "It takes (only) two: Adversarial generator-encoder networks." In *Thirty-Second AAAI Conference on Artificial Intelligence*. 2018.

[8] Donahue, Jeff, Philipp Krähenbühl, and Trevor Darrell. "Adversarial feature learning." *arXiv preprint arXiv:1605.09782* (2016).

[9] Dumoulin, Vincent, Ishmael Belghazi, Ben Poole, Olivier Mastropietro, Alex Lamb, Martin Arjovsky, and Aaron Courville. "Adversarially learned inference." *arXiv preprint arXiv:1606.00704* (2016).

[10] Mao, Xudong, Qing Li, Haoran Xie, Raymond YK Lau, Zhen Wang, and Stephen Paul Smolley. "Least squares generative adversarial networks." In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2794-2802. 2017.

[11] Mao, Xudong, Qing Li, Haoran Xie, Raymond YK Lau, Zhen Wang, and Stephen Paul Smolley. "On the effectiveness of least squares generative adversarial networks." *IEEE transactions on pattern analysis and machine intelligence* 41, no. 12 (2018): 2947-2960.

[12] Zhao, Junbo, Michael Mathieu, and Yann LeCun. "Energy-based generative adversarial network." *arXiv preprint arXiv:1609.03126* (2016).

[13] Che, T., Y. Li, A. P. Jacob, Y. Bengio, and W. Li. "Mode regularized generative adversarial networks." (2017).

[14] Salimans, Tim, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. "Improved techniques for training gans." In *Advances in neural information processing systems*, pp. 2234-2242. 2016.

[15] Heusel, Martin, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. "Gans trained by a two time-scale update rule converge to a local nash equilibrium." In *Advances in neural information processing systems*, pp. 6626-6637. 2017.

[16] Che, Tong, Yanran Li, Athul Paul Jacob, Yoshua Bengio, and Wenjie Li. "Mode regularized generative adversarial networks." *arXiv preprint arXiv:1612.02136* (2016).

[17] Bińkowski, Mikołaj, Dougal J. Sutherland, Michael Arbel, and Arthur Gretton. "Demystifying mmd gans." *arXiv preprint arXiv:1801.01401* (2018).

[18] Kurach, Karol, Mario Lucic, Xiaohua Zhai, Marcin Michalski, and Sylvain Gelly. "A large-scale study on regularization and normalization in GANs." *arXiv preprint arXiv:1807.04720* (2018).

[19] Yu, Lantao, Weinan Zhang, Jun Wang, and Yong Yu. "Seqgan: Sequence generative adversarial nets with policy gradient." In *Thirty-First AAAI Conference on Artificial Intelligence*. 2017.

[20] Lin, Kevin, Dianqi Li, Xiaodong He, Zhengyou Zhang, and Ming-Ting Sun. "Adversarial ranking for language generation." In *Advances in Neural Information Processing Systems*, pp. 3155-3165. 2017.