# GAN proposal

## GAN in general

Collecting datasets in scientific research usually faces challenges such as physical limitations of instruments or extensive labor requirements. Using deep learning models to automatically generating data or augmenting existing data is a new area worth investigate. Generative adversarial networks (GANs) [1] attract great attentions recently and have seen significant progress [2]–[5]. GANs proposed to generative tasks through a minimax game between two competing networks, the generator and discriminator, and such a methodology have great success on computer vision datasets [6]. Scientific datasets, however, expose unique challenges that require more research efforts to achieving good results with GANs.

## Development of GANs

The GAN structure proposed in [1] usually suffers from unstable training and mode dropping in generated samples [7]. Recent theoretical works on GANs mainly focus on stabilizing the training procedure of GANs [8], [7] and increasing both the quality and the diversity of generated samples [2]. On the other hand, a more interesting trend is to apply various neural network structures to improve GANs’ performance on different tasks.

There are several noticeable works among a great number of research efforts following this trend. Conditional GANs [3], [9] seek to teach GANs the ability to generate samples of a specific class, e.g., output samples of a specific hand writing number, by adding class information either to the input of the network or change the binary discriminator to a classifier. DCGAN [10] replaces the multi-layer perceptron networks with convolutional networks and achieves very good results on image datasets. There are also several works that use an encoder-decoder network structure as the generator that allow GANs manipulate a input image in different ways such as translating the input image to a different style [4], [11], rotating the image to an unseen angle [5], [12]. It is also possible to augment the input dataset with GANs to generate better samples. For example, a recent work using a gradually growing network structure for GANs to achieve super resolution photo realistic image [13]. Another work uses a stacked GAN structure [14] to translate text first into low resolution images and then augment it to high resolution images.

## GANs for scientific datasets

Compared to the great success of GANs in computer vision fields, the potential of GANs in other fields such as environmental science, biology and industrial engineering is yet to discover. There are some preliminary works to applying deep learning techniques on biology datasets [15], [16] that show great potentials in generating data, augmenting data and processing data. Auto-encoders have been used to generate chemical structures of molecules [18]. 3DGAN [17] that can generate 3D models from 2D images is of great interest for industrial engineering. Judging by its huge success on computer vision datasets, we believe applying GANs to dealing with issues of scientific datasets will be of great interest in the near future and significantly advance the related field.

## References

[1] I. J. Goodfellow et al., “Generative Adversarial Networks,” pp. 1–9, 2014.

[2] M. Arjovsky, S. Chintala, and L. Bottou, “Wasserstein GAN,” 2017.

[3] M. Mirza and S. Osindero, “Conditional Generative Adversarial Nets,” pp. 1–7, 2014.

[4] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, “Image-to-Image Translation with Conditional Adversarial Networks,” 2016.

[5] L. Tran, X. Yin, and X. Liu, “Disentangled Representation Learning GAN for Pose-Invariant Face Recognition,” Int. Conf. Comput. Vis. Pattern Recognit., pp. 1415–1424, 2017.

[6] Jia Deng, Wei Dong, R. Socher, Li-Jia Li, Kai Li, and Li Fei-Fei, “ImageNet: A large-scale hierarchical image database,” 2009 IEEE Conf. Comput. Vis. Pattern Recognit., no. June, pp. 248–255, 2009.

[7] M. Arjovsky and L. Bottou, “Towards Principled Methods for Training Generative Adversarial Networks,” pp. 1–17, 2017.

[8] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, “Improved Training of Wasserstein GANs,” 2017.

[9] A. Odena, C. Olah, and J. Shlens, “Conditional Image Synthesis With Auxiliary Classifier GANs,” 2016.

[10] A. Radford, L. Metz, and S. Chintala, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks,” pp. 1–16, 2015.

[11] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks,” 2017.

[12] A. Ghodrati, X. Jia, M. Pedersoli, and T. Tuytelaars, “Towards Automatic Image Editing: Learning to See another You,” 2015.

[13] T. Karras, T. Aila, S. Laine, and J. Lehtinen, “Progressive Growing of GANs for Improved Quality, Stability, and Variation,” pp. 1–25, 2017.

[14] H. Zhang et al., “StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks,” pp. 5907–5915, 2017.

[15] A. Osokin, A. Chessel, R. E. C. Salas, and F. Vaggi, “GANs for Biological Image Synthesis,” pp. 2233–2242, 2017.

[16] M. Weigert et al., “Content-Aware Image Restoration: Pushing the Limits of Fluorescence Microscopy,” bioRxiv, p. 236463, 2017.

[17] J. Wu, C. Zhang, T. Xue, W. T. Freeman, and J. B. Tenenbaum, “Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling,” no. Nips, 2016.

[18] Gómez-Bombarelli, Rafael, et al. "Automatic chemical design using a data-driven continuous representation of molecules." ACS Central Science (2016).