SGN-26006 Advanced Signal Processing Laboratory

Generative Adversarial Networks

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Background

The objective of this experiment is to let you familiarize basic Generative Adversarial Networks (GANs). Generative Adversarial Networks was proposed in 2014 by Ian [1] , which have been achieving significant outcomes in various machine learning tasks, such as image segmentation, audio synthesis, video prediction.

Generally, the GANs [1] are designed to include a generative model G and a discriminative model D. The main task of the discriminator D is to evaluate whether the data come from the real data distribution p_{data} or from a data distribution p_G generated by the generator G. During the training process, it aims to maximize the accuracy of discriminating the real data and the generated data, assigning 1 for the real data and 0 for the generated data. On the contrary, the generator G generates fraud data using a random vector $z \sim \mathcal{U}[-1, 1]$ as input. Its objective is to generate data that appears so authentic that the discriminator D is not able to discriminate it from the real data. These models acting against each other with the opposite goals bring GANs its name. In the training process of GANs, D and G are optimized alternately. When G is optimized, D is fixed and vice versa. The vanilla topology of GANs is shown in Fig. 1.

The objective function of the GANs is a zero-sum game between the generator G and the discriminator D, which can be considered also as a minimax two-player game. GANs is trained by optimizing the following loss function [1]:

$$\underset{G}{min}\, \underset{D}{max}\, V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{data}(\mathbf{x})}[log(D(\mathbf{x}))] + \mathbb{E}_{\mathbf{z} \sim p_z(\mathbf{z})}[log(1 - D(G(\mathbf{z})))]. \tag{1}$$

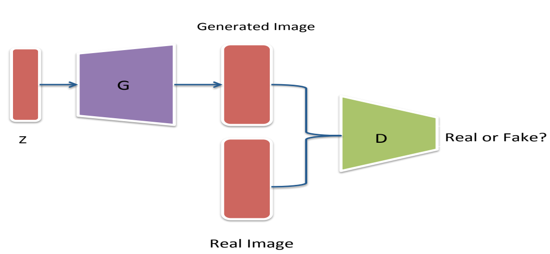

Figure 1: Topology of vanilla GANs structure

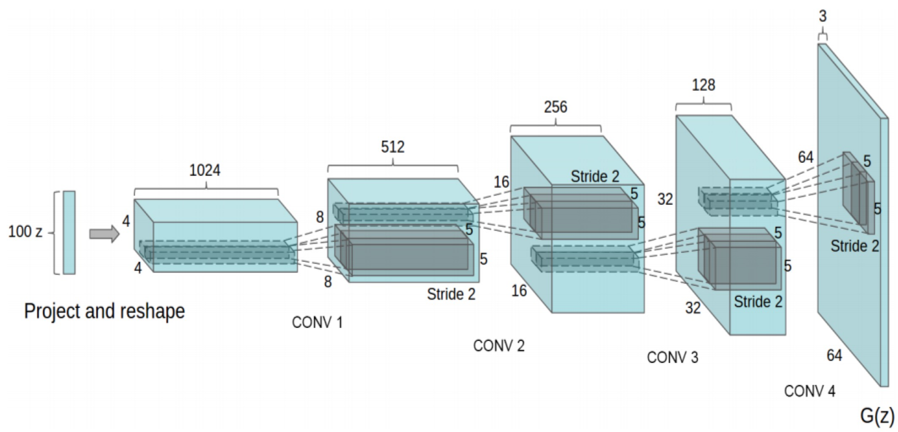

Figure 2: Topology of DCGANs structure

Deep Convolutional Generative Adversarial Networks (DCGAN) [2] is an extension of GANs, which introduces convolutional networks into its topology for unsupervised training. DCGANs utilize the powerful feature extraction capabilities of the convolutional network to improve learning results. The topology of DCGAN is demonstrated in Fig. 2.

Tasks

- Reading GANs and DCGANs related papers and other materials to learn more about GANs/DCGANs.
- Implementing vanilla GANs and DCGANs with MNIST dataset `http://yann.lecun.com/exdb/mnist/` to generate fraud digits by keras/Tensorflow/pyTorch.
- Comparing the pros and cons of GANs and DCGANs
- Writing a report about your understandings about GANs/DCGANs; moreover, explaining the differences of the two topologies and illustrating experiment processing.
- Returning your code and report in a zip file to Moodle before the given deadline.

Instructor The instructor of this experiment is Lei Xu (lei.xu@tut.fi).

References

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative Adversarial Networks. In *Int. Conf. on Neural Information Processing Systems (NIPS)*, proceedings, 2014.

[2] A. Radford, L. Metz, and S. Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. In *Int. Conf. on Learning Representations (ICLR)*, proceedings, 2016.