Insights, resources, and application of GAN

BY YALIN LIAO

The classical answer to learn a probability distribution is to define a parametric family of densities and find the one that maximizes the liklihood or posterior on the observed data. In the paper Generative Adversarial Nets (GANs), a novel framework, in the form of the mini-max game, is proposed to estimate generative models. For particular, the generator G is trained to fool the discriminator D while the discriminator D is optimized to distinct fake data generated by G from real samples. During training, G and D alternatively update with backpropagation , and finally, the entire system reaches the Nash-equilibrium (a state where G and D cannot further improve their performance).

The advantages of GANs

(1) Can quickly generate high quality samples as much as possible. You know by the traditional method, even if we have obtained a perfect approximator of the data density function, often it is not easy to sample data points from the density function.

(2) As mentioned in the paper, no Markov chain or inference is required.

The disadvantages of GANs

(1) Difficult to train a GAN

(2) Tend to suffer mode collapse issue

(3) No explicit representation to approximate the data density function

Some thinking

(1) If using mixture models to sample latent variable Z, instead of Gaussian or uniform distribution, what will happen? Generate more diverse samples?

(2) Can increasing the mini-batch size help get rid of the mode collapse issue? Intuitively the answer is yes because in each iteration the generator could see “a bigger word”.

(3) One reason for mode collapse is that the generator is not expressive enough. Can we borrow ideas from ensemble learning, like gradient boosting, to design more powerful generators?