Your 598 ID: 5107

Title of paper: "Improved Techniques for Training GANs" by Salimans et al.
What is their primary result? The authors propose a variety of 'new' architectural features and training procedures for generative adversarial networks (GANs) inspired by Game Theory. They then proceed to apply these to semi-supervised learning and the generation of visually realistic images.
Why is this important? As was remarked in the last paragraph, one of the main motivations for studying GANs is their effectiveness in creating images which humans find realistic. However, more interesting is the theoretical aspects of using GANs for semi-supervised learning applications as is noted in work of Sutskever–Jozefowicz–Gregor and Springenberg on unsupervised and semi-supervised networks.
What are their key ideas? This paper introduces several techniques to solve a difficult nonconvex optimization *game* with high-dimensional parameters. In such a situation, traditional methods such as that of (stochastic) gradient descent fail to converge. The authors introduce several techniques to 'encourage convergence.'

In the applications discussed in the paper, some or all of the following techniques are employed.

The first of these is *feature matching* which, roughly speaking, prevents the GAN from overtraining on a given discriminator by specifying a new objective for the generator.

The second of these, *minibatch discrimination*, addresses the situation where a GAN will collapse to a parameter setting where it emits the same point. When such a collapse is imminent, minibatch discrimination tells the outputs of the generator to become more dissimilar to each other.

The third is *historical averaging*, whereby each player's loss function includes the term $\|\theta - t^{-1}\sum_{i=1}^{t}\theta_i\|^2$ for θ_i the value of parameters at a past time i. This is inspired by the success of the Fictitious Play Algorithm at finding equilibria in other kinds of games.

The last two techniques are *one-sided label smoothing* and *virtual batch normalization.*
What are the limitations, either in performance or applicability? Virtual batch normalization is an expensive procedure since it requires each running forward propagation on two minibatches of data.
What might be an interesting next step based on this work? The authors use their techniques to make GANs learn to generate objects resembling animals. However, these animals lack any recognizable features of animals, such as heads, limbs, and appear rather as a mess of fur. It would be interesting to see in what way the model needs to be altered to generate recognizable anatomy in this application.
What's the architecture? They use a nine-layer deep convolutional network with dropout and weight normalization for the discriminator and a four-layer deep CNN with batch normalization for the generator.
How did they train and evaluate it? They test their semi-supervised learning task on MNIST, CIFAR-10, and SVHN by generating samples very similar to those found in the datasets and asking MTurk annotator to distinguish the real from fake data. On the MNIST dataset, annotators were able to distinguish GAN-generated samples from true samples in 52.4% of cases (only slightly better than randomly guessing). For the CIFAR-10, annotators correctly categorized 78.7% of all images.
Did they implement something? Several of the networks in this paper are available at https://github.com/openai/improved_gan.
Grader's 598 ID: