Paper

- **Title:** Generative Multi-Adversarial Networks
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- **arXiv link:** https://arxiv.org/abs/1611.01673

TL;DR

The paper shows how to use multiple Discriminators to train a GAN in order to train them faster. Generative Multi-Adversarial Networks(GMAN) also generates better images when compared by a GAM-type metric. Generative multi adversarial metric(GMAM) is also introduced to perform pairwise evaluation of separately trained frameworks

GMAN

They explore approaches ranging between two extremes: 1) a more discriminating D and 2) a D better matched to the generator's capabilities. Mathematically, reformulate G's objective as $\underset{G}{min}\ maxF(V(D_1, G), ..., V(D_N, G))$ where V is the classical GAN loss for different choices of F. F could be any differentiable aggregation function like max, mean.

Maximizing V(D, G)

For a fixed G, maximizing $F_G(V_i)$ with F as the max function is equivalent to optimizing V with random restarts in parallel and then presenting $max_{i \in \{1,...,N\}} V(D_i, G)$ as the loss to the Generator. Requiring the generator to minimize the max forces G to generate samples that must fool all N discriminators, each potentially representing a distinct max. Taking the max can also be seen as boosting the online prediction of the discriminator.

Soft Discriminator

In practice, training against a far superior discriminator can impede the generator's learning. So, they consider the following three classical Pythagorean means parameterized by λ where $\lambda = 0$ is the mean and $\lambda \to \infty$ corresponds to the max:

$$AM_{soft}(V,\lambda) = \sum_i^N w_i V_i$$

$$GM_{soft}(V,\lambda) = -exp(\sum_i^N w_i log(-V_i))$$

$$HM_{soft}(V,\lambda) = \left(\sum_i^N w_i V_i^{-1}\right)^{-1}$$

where w_i is the softmax.

GMAM

In GMAN, the opponent may have multiple discriminators, which makes it unclear how to perform the swaps needed for GAM.

$$GMAM = log\left(\frac{F^a_{G_b}(V^a_i)}{F^a_{G_a}(V^a_i)} \Bigg/ \frac{F^a_{G_a}(V^b_i)}{F^b_{G_b}(V^b_i)}\right)$$

where a and b refer to the two GMAN variants. The idea here is similar. If G2 performs better than G1 with respect to both D1 and D2, then GMAM ¿ 0. If G1 performs better in both cases, GMAM ¡ 0, otherwise, the result is indeterminate.