A study of quality and diversity in K+1 GANs

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Abstract

We study the K+1 GAN paradigm which generalizes the canonical true/fake GAN by training a generator with a K+1-ary classifier instead of a binary discriminator. We show how the standard formulation of the K+1 GAN does not take advantage of class information fully and show how its learned generative data distribution is no different than the distribution that a traditional binary GAN learns. We then investigate another GAN loss function that dynamically labels its data during training, and show how this leads to learning a generative distribution that emphasizes the target distribution modes. We investigate to what degree our theoretical expectations of these GAN training strategies have impact on the quality and diversity of learned generators on real-world data.

1 Introduction

When GANs were first introduced [1], deep learning had already had striking successes with learning discriminative models while high quality deep generative models had yet to appear. The GAN framework combined these two models in an adversarial setting that allowed the successes of discriminative models to be used to train generative models that produced realistic samples. The first GAN pitted a two class real/fake discriminator against a generator network and real images [1]. Since then a multitude of innovations in the architectures of these networks, and loss functions for how to combine them, have flourished [2], with the chief goals of improving sample diversity and quality [3].

Many works have found new ways to incorporate class information into the GAN training process to improve image generation [4, 5, 6, 7, 8, 9]. In this work we focus on K+1 GANs which combine the task of real/fake discrimination with class discrimination directly [9]. K+1 GANs proved most successful in improving semi-supervised learning classification performance [9, 10, 7], but have more recently been challenged by a different class of methods [11, 12]. They have never been as widely successful as GANs with auxiliary classifiers (ACGAN) [4], or GANs that use class embeddings without the classification task [6, 13, 14]. Here we investigate why the GAN architecture which most closely unifies real sample classification with fake sample classification has been overtaken by other methods.

We study a hypothesis testing inspired extension of the binary GAN into the K+1 setting [9], where K real distributions are classified against each other, and against a fake distribution. We show how the optimal discriminator/classifier in this setting is a straightforward generalization of the optimal binary GAN discriminator, and show that the formulation of the log likelihood loss prevents the generator from fully benefiting from supervision over the classes of real samples. Then we then introduce another generator loss criterion that uses dynamic labeling [7], and describe how it has increased class specificity over the K+1 GAN by emphasizing the modes of the real data. Finally we demonstrate with experiments on CelebA and CIFAR10 to what degree both GAN formulations have an effect on increasing the quality and diversity of samples over the original binary GAN and more popular ACGAN.

Submitted to 1st I Can't Believe It's Not Better Workshop (ICBINB@NeurIPS 2020). Do not distribute.

2 Background

2.1 Binary GANs and K+1 GANs

The generalization of the binary GAN [1], known as the K+1 GAN (and also as LabelGAN [7]), was originally developed for semi-supervised learning with GANs [9]. We let $M = K + 1$ denote the total number of classes, K real classes plus the fake class, which we refer to as the zeroth class. This generalization echoes the form of the generalization of binary minimax hypothesis testing to be M-ary [15]. We use the notation that X, H, D, Z are respectively the images, hypotheses (fake, real class 1, real class 2, etc), decisions, and random codes. Our discriminator $d(x)$ outputs the vector $d_m(x) = \mathbb{P}[D = m|X = x], m = 0, 1, \ldots, M - 1$. The objective function of the binary GAN naturally generalizes to training all outputs of the discriminator:

$$\begin{aligned} \mathrm{L}_{\mathrm{K+1}}(d, g) &= \sum_{m=0}^{M-1} p_m \mathbb{E}[\log \mathbb{P}[D = m \mid X] \mid H = m] \\ &= \sum_{m=1}^{M-1} p_m \int \log d_m(x) f_m(x) dF(x) + p_0 \int \log d_0(g(z)) f_0(g(z)) dF(g(z)) \end{aligned} \tag{1}$$

We denote the fake and real densities as $f_h(x) = \mathbb{P}[X = x \mid H = h],\ h = 0, 1, \ldots, K$ and p_m is the prior on each hypothesis (often taken to be uniform). For every image x the optimal decision vector $d^*(x)$ exists and each of its M elements is given by $d^*_m(x) = p_m f_m(x) / \sum_{i=0}^{M-1} p_i f_i(x)$. This can be proved for discrete densities using the classic optimality criterion for differentiable convex objectives [16]. Plugging in $d^*(x)$ into Equation (1) we see:

$$\begin{aligned} \mathrm{L}_{\mathrm{K+1}}(d^*, g) &= \sum_{m=0}^{M-1} \int \log \frac{p_m f_m(x)}{f_{\mathrm{avg}}(x)} p_m f_m(x) dF(x) \\ &= \sum_{m=0}^{M-1} KL(f(\cdot, m) \mid\mid f_{\mathrm{avg}}(\cdot)) \end{aligned} \tag{2}$$

where $f_{\mathrm{avg}}(x) = \sum_{m=0}^{M-1} p_m f_m(x)$. The task of the generator is $\min_{f_0} \mathrm{L}_{\mathrm{K+1}}(d^*, g)$, which for discrete PMFs f_m is a convex optimization problem, the solution is $p_0 f_0(x) \rightarrow f_{\mathrm{real}}(x) = \sum_{m=1}^{M-1} p_m f_m(x)$. This is consistent with the result from [1] for $M = 2$ and $p_0 = p_1 = 1/2$.

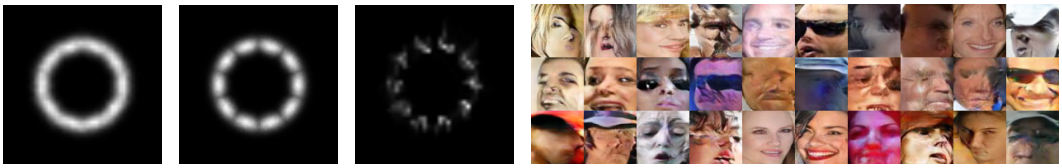
The typical intuition in training neural networks is that learning from more data and sharing parameters across tasks leads to better performance. But here, surprisingly the theory states that by using class information in the $K + 1$ GAN to train a discriminator that can discriminate between classes, and between fake images and each of the classes, is no better than ignoring the class information. That is, if we have labeled classes for data, but choose to throw it away by merging $f_1, \ldots, f_K$ into a single f_{real}, the generator of the binary GAN that we train should have the same distribution f_0 as if we trained the K+1 GAN. This result is also consistent with examining the gradients of the K+1 GAN which reveal a "overlaid-gradient" problem whereby the overall gradient w.r.t. a generated example is the same as that in the binary GAN [7].

The $K + 1$ GAN's original purpose was however to improve the state of the art in semi-supervised classification [9], rather than improve generation of images (though human annotators were said to prefer images from a K+1 GAN). We note that in Equation (1) we omitted the part of the loss for unlabeled real images. Nevertheless we have shown that counter-intuitively, training a fully supervised $K + 1$ discriminator to classify the real examples in parallel with telling fake examples apart from real examples does not change the generator learned.

2.2 Dynamic Labeling and Mode Emphasizing GAN

One extension that increases the class specificity of the generator learned by a K+1 GAN is to introduce dynamic labeling [7]. Such a choice leads to f_0 converging to emphasize the modes of $f_1, \ldots, f_K$, rather than being the average of them f_{real}.

Looking at the last integral in Equation (1), we notice that the g^* that solves $\min_g \mathbb{E}[\log \mathbb{P}[D = 0 \mid X] \mid H = 0]$ also solves $\min_g -\mathbb{E}[\log \mathbb{P}[D \neq 0 \mid X] \mid H = 0] = \min_g -\mathbb{E}[\log \sum_{m>0} \mathbb{P}[D = m \mid$



(i) Data (ii) f_0 Expected (iii) f_0 Learned (iv)

Figure 1: Mode emphasis of Dynamic Labeling GAN. (i) shows 10 overlapping classes of 2D Gaussian data arranged on a circle within $(0, 4) \times (-1, 5)$. (ii) shows the PMF that is the solution of the convex upper-bound of Equation (3), this is the distribution that we expect a GAN trained with $\mathrm{L}_{\mathrm{Dyn}}$ to learn. (iii) shows the histogram of a generator trained with $\mathrm{L}_{\mathrm{Dyn}}$. (iv) shows a random selection 10 images from each GAN that have a MTCNN confidence of 0. The first row from is from a binary GAN, the second row is from ACGAN, and the third row from Dynamic Labeling GAN. This shows that even if modes are emphasized, this does not necessarily mean samples are not realized in what could be considered undesirable low density regions of f_{real}.

$X] \mid H = 0]$. This equivalence provides the intuition for why the density of the generator will be the average of all the real distributions. Let: $\mathrm{L}_{\mathrm{Dyn}}(d, g) = -\mathbb{E}[\log \max_{l>0} \mathbb{P}[D = l \mid X] \mid H = 0]$. That is for each fake $g(z)$ we look at the "most likely mistake" the discriminator makes $d(g(z))$, and train g to emphasize it. For d we keep the K+1 GAN objective unchanged. If we let d^* be optimal in the sense of the previous section, then

$$\min_g \mathrm{L}_{\mathrm{Dyn}}(d^*, g) = \min_g KL(f_0 \mid\mid \text{ptwise} \max_{m>0} f_m) - KL(f_0 \mid\mid f_{\mathrm{avg}}) \tag{3}$$

Comparing this to Equation (2), our intuition expects $f_0(x) \approx \max_{m>0} f_m(x)$ with Dynamic Labeling instead of $f_0(x) = \sum_{m>0} f_m(x)$ in K+1 GAN for the following reason. We note that $\min_{f_0} KL(f_0 \mid\mid \text{ptwise } \max_{m>0} f_m)$ upper bounds Equation (3), for discrete PMFs it is a convex optimization problem, and the solution is $f_0(x) \to \max_{m>0} f_m(x)$.

Dynamic labeling GAN was found to be experimentally preferable to competing non-dynamically labeled GANs in the sense of Inception Score (IS) [7]. Our analysis here, which looks at the unconditional K+1 GAN with dynamic labeling, explains why but also reveals a potential failure mode. IS is proportional to the KL divergence of $\mathbb{P}(Y|X)$ and $\mathbb{P}(Y)$ for images X and labels Y from a pretrained Inception v3 network [9, 17]. Thus a generator that emphasizes all the modes (classes) of the real data distribution should generate easily recognizable images and have low entropy $\mathbb{P}(Y|X)$ and have a high entropy $\mathbb{P}(Y)$ by displaying all the classes, giving a high IS. However emphasizing the modes of the data could also result in lower observed diversity from finite samplings of g since the density of f_0 is concentrated around the modes. For this reason we also refer to this GAN as "Mode GAN".

3 Experiments and Discussion

3.1 Methods

We demonstrate our findings on K+1 GANs using three datasets: synthetic 2D Gaussians, CelebA, and CIFAR10. Our Gaussian data is created from 10 highly overlapping 2D Gaussians whose means are distributed uniformly on a circle, samples from different Gaussians are different "classes". Samples from all the classes are shown in Figure 1i. CelebA is a dataset with 40 binary attribute annotations and 5 landmark locations. The images we use are 64×64 and have the background cropped. We split this dataset into 5 classes: Front facing female/male with mouth open/closed are 4, and all faces rotated more than 15 degrees are the 5th. CIFAR10 is a 32×32 dataset with 10 classes. We use all 50,000 images for training, and the 10 classes are the labels for our supervised models.

We train three SN GAN networks [13] (Binary GAN, ACGAN, Mode GAN) with default hyperparameters and only vary the loss function used. We also train two additional SN GAN networks (Mode GAN and K+1 GAN) that also used projection discrimination [18]. All networks were trained for 200k iters for CelebA and 500k iters for CIFAR10.

Method	**FID** CelebA	**IS** CIFAR-10
SN GAN	4.13	8.03
SN ACGAN	5.07	8.02
SN Mode GAN	3.65	8.13
PJ SN Mode GAN		8.50
PJ SN K+1 GAN		8.43

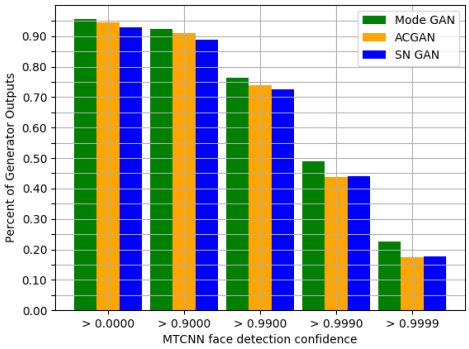


Figure 2: On the left are FIDs image generation on CelebA and Inception scores for CIFAR-10. On the right is the percentage of 100,000 samples generated by each GAN for which MTCNN has greater than c confidence that a face is present, where $c = 0, 1-10^{-1}, 1-10^{-2}, 1-10^{-3}, 1-10^{-4}$. We use the publicly available pretrained MTCNN face detector network to compute the confidence scores.

3.2 Discussion

When the form of the true densities $f_m(x)$ are known, we can observe the learned density of the generator f_0 via the histogram of its samples. For the Dynamically Labeled GAN we see the PMF that minimizes the convex upper-bound of Equation (3) in Figure 1ii emphasizes the modes of the data. In Figure 1iii we see that the learned g from minimizing Equation (3) while training a GAN indeed emphasizes the modes of the data: the samples are in high density around the means of each class, and are low density in the overlap between classes. However, this simple example does not generalize neatly to real data. We may expect an analogous situation in the domain of faces to be that few samples exist between the "means" of the 5 classes we chose: i.e. no interpolations between males facing left and females facing right. But we see in Figure 1iv that Dynamically Labeled GAN generates unwanted low quality samples just like the baseline Binary GAN and ACGAN networks.

To measure the quality of our CelebA GAN's output, we use the confidence output of MTCNN, a publicly available pretrained face detector, to measure the frequency of bad generator samples. In Figure 1iv are examples of images that MTCNN assigns 0 confidence output by all 3 GANs. For images that are far away from the modes of the CelebA data density, for example images that blur together multiple face orientations into 1 image, MTCNN will assign a low confidence. The right hand side of Figure 2 shows out of 100,000 samples generated by each GAN, the percentage of images with MTCNN confidence greater than $c = 0, 1-10^{-1}, \ldots, 1-10^{-4}$ is always largest in Mode GAN, but only by a small margin. And as shown in the figure, all the networks produce a score 0 face 4-6 times every 10000 images.

The left hand side of Figure 2 shows that performance was tied for the three networks on CelebA and CIFAR10. Adding projection discrimination (PJ) to the networks yeilded a much greater difference in IS performance than the changes in loss function. We show some samples from the CIFAR10 GANs in Figure 3, which are hard to qualitatively rank.

To measure diversity within a batch of generated images, we embed the images in a feature space with an auxiliary network, calculate all the pairwise distances, and record the mean. In Figure 3iv we see Mode GAN always has a higher mean pairwise distance only within a margin of error. Thus we don't observe that fitting the modes of real data yields a big impact on quality or diversity of samples.

4 Conclusion

This work provided a hypothesis testing perspective on the canonical binary GAN, its K+1 GAN generalization, and an extension meant to increase the class specificity during training, Dynamically Labeled GAN. We showed that the GAN's generator is not benefited by the classification of real vs real samples in K+1 GANs. And we demonstrated that Dynamically Labeled GAN emphasizes the

(i) SNGAN (ii) ACGAN (iii) Mode GAN (iv) CIFAR10

Figure 3: Generated images on CIFAR10 for the three methods we compare. Images are randomly selected from each generator and sorted by class by an auxiliary DenseNet121 classifier with 95% test accuracy into the 10 classes of CIFAR10: plane, car, bird, cat, deer, dog, frog, horse, ship, truck. In iv we plot the mean pairwise distance of the outputs of the three GANs. That is for each image in a batch of size in the range $n * 128, n = 1, 2, \ldots, 79$ an embedding was generated by an auxiliary network, and then the pairwise Euclidean distances were computed. For each of these 79 batches of increasing size the mean embedding distance per generator was recorded. In each plot the average of 10 trials is shown with the standard deviation shaded. The embedding network was the 1,024 dimension penultimate layer of a DenseNet-121.

modes of the real data distributions, but this has a tenuous link to increased quality and diversity of generated samples.

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