Omni-GAN: On the Secrets of cGANs and Beyond

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Abstract

It has been an important problem to design a proper discriminator for conditional generative adversarial networks (cGANs). In this paper, we investigate two popular choices, the projection-based and classification-based discriminators, and reveal that both of them suffer some kind of drawbacks that affect the learning ability of cGANs. Then, we present our solution that trains a powerful discriminator and avoids over-fitting with regularization. In addition, we unify multiple targets (class, domain, reality, etc.) into one loss function to enable a wider range of applications. Our algorithm, named Omni-GAN, achieves competitive performance on a few popular benchmarks. More importantly, Omni-GAN enjoys both high generation quality and low risks in mode collapse, offering new possibilities for optimizing cGANs. The code is available¹.

1. Introduction

Generative Adversarial Networks (GANs) [10] are powerful tools for image generation [1, 15, 24] and domain adaptation [3, 14, 22, 38]. The big family of GANs can be roughly divided into two parts, unconditional GANs [17, 18] and conditional GANs (cGANs) [23, 2], differing from each other in whether the class labels (e.g., face, car, flower, etc.) are used for image generation. It is well acknowledged that cGANs enjoy both higher potentials and higher risks in the training stage. As shown in Fig. 1, BigGAN [2] and Multi-hinge GAN [19], two cGAN variants, achieve higher Inception score (IS) [33] than StyleGAN [18], an unconditional counterpart, but the curves drop dramatically at some point of training (a.k.a. mode collapse). This makes the cGAN training procedure unstable and early termination is often required to achieve satisfying performance.

As noticed by the community [16], the instability of the training procedure is highly related to the discriminator, i.e., the module that outputs a probability indicating the reality of the generated image. We further categorize the existing discriminators for cGANs into two types, namely, projection-based [25, 2] and classification-based [27, 19], by whether the discriminator is required to output an explicit class label for each image. We find that, although the former (i.e., projection-based, with a weaker, implicit discriminator) are inferior to the latter in terms of the Inception score, the latter are prone to mode collapse (e.g., in Fig. 1, Multi-hinge GAN achieves a higher Inception score but collapses earlier). This makes us to consider the relationship between the training stability and the strength of the discriminator.

The main discovery of this paper is that classification-based and projection-based discriminator can be unified using a multi-label classification loss [35]. This offers us an opportunity to observe the advantages and disadvantages of both options. As a result, we find that using a strong discriminator (in particular, the classification-based one) and equipping it with proper regularization (to prevent it from quickly memorizing the training image set) is the best choice, where the GAN model enjoys high quality in image generation yet has a low risk of mode collapse. Based on

¹https://github.com/PeterouZh/Omni-GAN-PyTorch

Figure 1: Inception score (IS) of unconditional GANs and conditional GANs on CIFAR100. Omni-GAN enjoys both high generation quality and a low risk of mode collapse.
the strong supervision, regularization is easily added to the classification-based loss function in the form of a weight decay that only requires a few lines of code. We name the proposed algorithm **Omni-GAN**.

Omni-GAN has the ability to integrate multiple discrimination tasks, including object classification, domain classification, and reality judgment (the adversarial term), into one objective, which further simplifies the deployment by getting rid of tuning multiple hyper-parameters. In extensive experiments, we demonstrate the competitive performance of Omni-GAN on (i) CIFAR [20] and ImageNet [7], two standard benchmarks for conditional image generation, (ii) Cityscapes [5], an image-to-image translation task converting a semantic segmentation mask to a photorealistic image, and (iii) the mixed MNIST [21] and SVHN [26] dataset to verify the ability of fitting different domains. Omni-GAN shows a stronger ability in resisting mode collapse, e.g., compared to BigGAN, the safe area (keeping a high Inception score) is augmented by at least two times. These results verify that making full use of supervision can improve the generation quality at the risk of easier mode collapse, yet weight decay, a simple regularization method, is effective to avoid the collapse and thus achieve superior performance.

2. Preliminaries

2.1. Conditional GANs

Conditional GAN (cGAN) [23] adds conditional information to the generator and discriminator of GANs. There are some ways to incorporate class information into the generator, such as conditional batch normalization (CBN) [6], conditional instance normalization (CIN) [9, 12], class-modulated convolution (CMConv) [44], etc. There are also different ways to add class information to the discriminator. A simple way is to directly concatenate the class information with the input or features from some middle layers [8, 31, 42, 29, 32]. Next, we expound on several slightly complicated methods.

**AC-GAN** Auxiliary classifier GAN (AC-GAN) [27] uses an auxiliary classifier to enhance the standard GAN model (see Fig. 2a). In particular, the objective function of both parts: the GAN loss, \( \mathcal{L}_{GAN} \), and the classification loss, \( \mathcal{L}_{cls} \):

\[
\mathcal{L}_{GAN} = \mathbb{E} \left[ \log P (g = \text{real} | x_{\text{real}}) \right] + \mathbb{E} \left[ \log P (g = \text{fake} | x_{\text{fake}}) \right],
\]

\[
\mathcal{L}_{cls} = \mathbb{E} \left[ \log P (g = c | x_{\text{real}}) \right] + \mathbb{E} \left[ \log P (g = c | x_{\text{fake}}) \right],
\]

where \( g \) denotes the label of \( x \). \( x_{\text{real}} \) and \( x_{\text{fake}} \) represent a real image and a generated image respectively. The discriminator \( D \) of AC-GAN is trained to maximize \( \mathcal{L}_{GAN} + \mathcal{L}_{cls} \), and the generator is trained to maximize \( \mathcal{L}_{cls} - \mathcal{L}_{GAN} \).

**Projection Discriminator** Projection discriminator [25] incorporates class information into the discriminator of GANs in a projection-based way (see Fig. 2b). The mathematical form of the projection discriminator is given by

\[
D(x, y) = y^T V f_1 (x; \theta_1) + f_2 (f_1 (x; \theta_1); \theta_2),
\]

where \( x \) and \( y \) denote the input image and one-hot label vector respectively. \( V \) is a class embedding matrix, \( f_1 (; \theta) \) is a vector function, and \( f_2 (; \theta) \) is a scalar function. \( V, \theta_1, \theta_2 \) are learned parameters of \( D \). The discriminator \( D \) only outputs a scalar for each pair of \( x \) and \( y \).

**Multi-hinge GAN** Multi-hinge GAN [19] uses a \( C + 1 \) dimensional classifier as the discriminator, which is trained by a multi-class hinge loss (see Fig. 2c). Let the classifier be \( S : \mathbb{X} \rightarrow \mathbb{R}^{C+1} \), the input image be \( x \), and the class label be \( y \in \{0, 1, \ldots, C-1\} \). We use \( s = S(x) \) to denote the score vector of input image \( x \). The \( C \)-th element of \( s \), \( s_C(s) \), indicates the score corresponding to the fake (with indexing starting at 0). The discriminator loss is given by

\[
\mathcal{L}_D = \mathbb{E}_{(x,y) \sim p_{data}} \left[ \max (0, 1 - s_y(x) + s_{-y}(x)) \right] + \mathbb{E}_{z \sim p_z, y \sim p_{data}} \left[ \max (0, 1 - s_C(G(z,y)) + s_{-C}(G(z,y))) \right].
\]

where \( s_y(x) \) denotes the element \( y \) of vector \( s \) and \( s_{-y}(x) = \max_{k \neq y} s_k(x), k \in \{0, 1, \ldots, C\} \setminus \{y\} \), represents the highest score except \( s_y(x) \). The generator loss consists of two parts:

\[
\mathcal{L}_G = \lambda \mathcal{L}_{GAN} + \mathcal{L}_{FM}
\]

\[
= \lambda \mathbb{E}_{z \sim p_z, y \sim p_{data}} \left[ \max (0, 1 - s_y(G(z,y)) + s_{-y}(G(z,y))) \right] + \|\mathbb{E}_{z \sim p_z, y \sim p_{data}} [S_{\text{feat}} (G(z,y))] - \mathbb{E}_{z \sim p_z} [S_{\text{feat}} (x)]\|_1.
\]

where the former is the multi-hinge adversarial loss, and the latter is a feature matching loss, which is able to alleviate the problem to some extent of training collapse earlier induced by the multi-hinge loss [19]. \( S_{\text{feat}}(\cdot) \) denotes extracting features by the classifier \( S \).

2.2. Unified Loss for Feature Learning

In fact, there is a unified perspective for classification tasks. We denote the positive scores as \( \{s_1^{(p)}, s_2^{(p)}, \ldots, s_K^{(p)}\} \), and negative scores as \( \{s_1^{(n)}, s_2^{(n)}, \ldots, s_K^{(n)}\} \), respectively. Sun et al. [36] proposed a unified loss to maximize \( s_i^{(p)} \) as well as to minimize \( s_i^{(n)} \). The loss is defined as

\[
\mathcal{L}_{\text{uni}} = \log \left[ 1 + \sum_{i=1}^K \sum_{j=1}^L \exp \left( \gamma (s_j^{(n)} - s_i^{(p)} + m) \right) \right] = \log \left[ 1 + \sum_{j=1}^L \exp \left( \gamma (s_j^{(n)} + m) \right) \right] \sum_{i=1}^K \exp \left( -\gamma s_i^{(p)} \right) \right),
\]

(6)
where $\gamma$ stands for a scale factor, and $m$ for a margin between positive and negative scores. Eq. (6) can be converted into triplet loss [34] or softmax with the cross-entropy loss (please refer to [36]).

3. Omni-GAN

In this section, we expound on Omni-GAN. Firstly, we define the omni-loss and show its ability to unify classification-based and projection-based cGANs (Sec. 3.1). Secondly, we show that the classification-based cGAN, Omni-GAN, suffers from early collapse problem existing in other classification-based cGANs such as Multi-hinge GAN. We propose a simple yet effective regularization to overcome this problem (Sec. 3.2). Subsequently, in Sec. 3.3, we evaluate a projection-based variant, one-sided Omni-GAN, substantiating that the superiority of Omni-GAN comes from fully utilizing class supervision. Finally, we show how to apply omni-loss to a fully convolutional discriminator (Sec. 3.4).

3.1. Unifying Classification-based and Projection-based cGANs

We commence from defining the omni-loss. Let $x$ and $y$ denote an image and its multi-label vector respectively. $S$ is a classifier. Suppose that there are $K$ positive labels and $L$ negative labels. Then $s = S(x)$ is a $K + L$ dimensional score vector. The omni-loss is defined as

$$L_{omni}(x, y) = \log \left(1 + \sum_{i \in I_{neg}} e^{s_i(x)}\right) + \log \left(1 + \sum_{j \in I_{pos}} e^{-s_j(x)}\right),$$

(7)

where $I_{neg}$ is a set consisting of indexes of negative scores (i.e., $|I_{neg}| = L$), and $I_{pos}$ consists of indexes of positive scores (i.e., $|I_{pos}| = K$). $s_k(x)$ represents the element $k$ of vector $s$. Next, we introduce two cases of combining omni-loss with cGANs.

The classification-based case. Combining omni-loss with the discriminator of cGANs derives a classification-based cGAN, Omni-GAN. We first elucidate the loss of the discriminator. The discriminator loss consists of two parts, one for $x_{real}$ (drawn from the training data), and the other for $x_{fake}$ (drawn from the generator). For $x_{real}$, its multi-label vector is given by

$$y_{real} = \frac{0, \ldots, 1_{gt}, \ldots, 0}{C},$$

(8)

where its dimension is $C + 2$, with $C$ being the number of classes of the training dataset. $1_{gt}$ is 1 if its index in the vector is equal to the ground truth label of $x_{real}$, otherwise 0. We use 1 to denote the corresponding score belongs to the positive set, and 0 to the negative set. The multi-label vector of $x_{fake}$ is also a $C + 2$ dimensional vector:

$$y_{fake} = \frac{0, \ldots, 0, \ldots, 0, 1_{fake}}{C},$$

(9)

where in this case it is a one-hot vector with only the last element being 1.

According to Eq. (7), (8), and (9), we define the discriminator loss as

$$L_D = \mathbb{E}_{x_{real} \sim p_d} \left[L_{omni}(x_{real}, y_{real})\right] + \mathbb{E}_{x_{fake} \sim p_g} \left[L_{omni}(x_{fake}, y_{fake})\right],$$

(10)

where $p_d$ is the training data distribution, and $p_g$ is the generated data distribution. In this setting, the discriminator $D$ actually acts as a multi-label classifier, which takes as input $x$, and outputs a score vector $s = D(x)$.

The generator attempts to fool the discriminator into believing its samples are real. To this end, its multi-label is set to

$$y_{fake}^{(G)} = \frac{0, \ldots, 1_G, \ldots, 0}{C},$$

(11)

which is the same as $y_{real}$ defined in Eq. (8). $1_G$ is 1 if its index in the vector is equal to the label adopted by the
generator to generate $x_{\text{fake}}$, otherwise 0. The generator loss is then given by

$$\mathcal{L}_G = E_{x_{\text{fake}} \sim p_g} \left[ \mathcal{L}_{\text{omni}} (x_{\text{fake}}, y_{\text{fake}}^{(G)}) \right]. \quad (12)$$

The projection-based case. We imitate the way how the projection-based discriminator [25] utilizes class labels (see Eq. (3)), and design a projection-based variant of Omni-GAN, named one-sided Omni-GAN, which does not fully utilize the class supervision.

It is easy to implement one-sided Omni-GAN: only slightly modify the multi-label vector, $y$. Following the setting above, the multi-label vector for $x_{\text{real}}$ is set to

$$y_{\text{real}} = \underbrace{1, \ldots, 1}_{C_1}, \ldots, -1, 1, -1. \quad (13)$$

where $1_{C}$ is 1 if its index in the vector is equal to the ground truth label of $x_{\text{real}}$, otherwise $-1$. And $-1$ means that the corresponding score will be ignored when calculating the omni-loss. The multi-label vector for $x_{\text{fake}}$ is given by

$$y_{\text{fake}} = \underbrace{-1, \ldots, 0}_{C_2}, \ldots, -1, 0, -1. \quad (14)$$

where $0$ if its index in the vector is equal to the label adopted by the generator to generate $x_{\text{fake}}$, otherwise $-1$. The discriminator loss is the same as that defined in Eq. (10).

For generator, its multi-label vector for $x_{\text{fake}}$ is

$$y_{\text{fake}}^{(G)} = \underbrace{-1, \ldots, 1}_{C_3}, \ldots, -1, 1, -1. \quad (15)$$

where $1_2$ is 1 if its index in the vector is equal to the label adopted by the generator to generate $x_{\text{fake}}$, otherwise $-1$. The generator loss is the same as that defined in Eq. (12).

In summary, we introduce two types of omni-GAN, which are derived by modifying the multi-label vector of the omni-loss (defined in Eq. (7)). It is easy to implement the omni-GAN in practice: as shown in Fig. 2d, first, let the discriminator output a vector instead of a scalar; second, apply the omni-loss to the output vector.

### 3.2. Avoiding Early Collapse

Like other classification-based cGANs, the Omni-GAN also suffers from early collapse during training. We conducted control experiments on CIFAR100 [20], and compared Omni-GAN with a projection-based cGAN, namely BigGAN [2]. As shown in Fig. 3a, the IS of the Omni-GAN shows a very exciting upward trend compared to the projection-based cGAN. However, unfortunately, the IS drops dramatically when about $1M$ real images (20 epoch) are shown to the discriminator, indicating that the training collapses earlier. The projection-based cGAN, BigGAN, also collapses when about $20M$ real images are shown to the discriminator (around 400th epoch).

**What causes the collapse?** Karras et al. [16] found that the discriminator overfits the training dataset, which will lead to incorrect gradients provided to the generator, so that the training diverges. To verify that the collapse of the above projection-based cGAN is due to the over-fitting of the discriminator, we plotted the scalar output of the discriminator, $D(x)$, over the course of training. We utilized the test set of CIFAR100 containing 10,000 images as the verification set, which was not used in the training.

As shown in Fig. 3b, obviously, as training progresses, the $D(x)$ of the validation set tends to that of the generated images, substantiating that the discriminator overfits the training data. We also plotted the FID curve in the same figure. It can be seen that when show about $20M$ real images (i.e., around 400 epoch) to the discriminator, the training commences diverging. The best FID is obtained when approximately $15M$ real images are shown to the discriminator.

**How to avoid the collapse?** To overcome the over-fitting
of the discriminator, Karras et al. [16] proposed to use data augmentation, a standard solution against over-fitting. In this paper, we propose to apply weight decay to the discriminator to alleviate the over-fitting of the discriminator. In Fig. 3c, we show the $D(x)$ and FID after applying weight decay to the projection-based discriminator. We can find that although the discriminator still overfits the training data, the training dose not collapse during the whole training process (the minimum FID, 9.74, is not reached until the end of the training).

Since weight decay can stabilize the training of the projection-based cGAN, can it stabilize the training of the Omni-GAN? We then applied weight decay to the discriminator of Omni-GAN, and plotted the IS curve in Fig. 3a. Excitingly, the early collapse disappears immediately, and the training process becomes very stable. Moreover, the IS is significantly better than the baseline methods (projection-based cGAN, BigGAN, with or without weight decay).

3.3. The Devil Lies in Supervision

Although the IS of Omni-GAN is much higher than that of the projection-based cGAN (BigGAN), the key factor driving this improvement is still unknown. We proceed to evaluate the one-sided Omni-GAN. One-sided Omni-GAN belongs to projection-based cGANs in that it does not fully utilize the class supervision. To compare fairly with the BigGAN, one-sided Omni-GAN did not use weight decay.

Fig. 3a shows the IS curve of one-sided Omni-GAN. We deliver two messages: one-sided Omni-GAN does not suffer from early collapse even if weight decay is not adopted; the IS of one-sided Omni-GAN is comparable to that of the projection-based cGAN (BigGAN), but it is worse than that of Omni-GAN. These phenomena substantiate that the notable performance of Omni-GAN comes from making full use of class supervision.

To sum up, our results reveal that fully utilizing the supervision can improve performance of cGANs, but at the risk of early collapse. This work offers a practical way (adding regularization) to overcome the collapse issue (there may exist other ways to achieve the same goal), so that the trained model enjoys both superior performance and safe optimization.

3.4. Generalization to Image-to-Image Translation

Omni-loss can be applied to a fully convolutional discriminator, which is widely adopted by image-to-image translation tasks [28, 13, 40]. As shown in Fig. 4, the discriminator is a fully convolutional network, which takes as input images and outputs feature maps with the number of channels being $C + 2$. $C$ represents the number of classes which is analogous to that of the semantic segmentation task. $2$ indicates there are two extra feature maps representing to what extent the input image is real or fake.

We adopt nearest neighbor downsampling to downsample the label map to the same resolution as the output feature maps of the discriminator. Then we use the downsampled label map as ground truth label, and apply a per-pixel omni-loss to the output feature maps of the discriminator. In Sec. 4.3, we will show that the per-pixel omni-loss can improve the performance of semantic image generation [39, 30].

4. Experiments

4.1. Evaluation and Implementation Details

Evaluation. We use Inception Score (IS) [33] and Fréchet Inception Distance (FID) [11] to measure the performance of GANs. In particular, we randomly generate $50K$ images and use the official TF inception v3 model [37] to calculate the metrics. The FID statistic files are pre-calculated using all training images. For semantic image synthesis, we follow the evaluation protocol adopted by previous works [4, 40, 28]. Specifically, we use a pre-trained semantic segmentation model to predict the semantic map of the synthesized images, and then use the mean Intersection-over-Union (mIoU) to measure the segmentation performance. The mIoU is used as the performance metric of the synthesized images.

Implementation Details. For cGAN model, we use Big-GAN\(^2\) as our baseline which employs a projection-based discriminator by default. We replace the unofficial evaluation code (i.e., using the PyTorch inception network to calculate IS and FID) with the official evaluation code (using the TF model) to monitor the training process. However, for ImageNet, we directly use the unofficial evaluation code for reasons of efficiency. For semantic image synthesis, we use

\(^2\)https://github.com/ajbrock/BigGAN-PyTorch
Figure 5: Omni-GAN achieves superior FID and IS at the same time. FQ-GAN looks good in terms of FID but with ordinary IS. Multi-hinge GAN is not stable and crashes on CIFAR100.

| Method       | CIFAR10 | CIFAR100 |
|--------------|---------|----------|
|              | FID ↓   | IS ↑     | FID ↓   | IS ↑     |
| SN-GAN [24]  | 15.73   | 18.87    | 8.19    | 8.19     |
| AC-GAN [27]  | 19.70↑  | 25.40↑   | 8.80↑   |          |
| cproj [25]   | 17.50↑  | 23.20↑   | 9.04↑   |          |
| BigGAN [2]    | 7.05    | 10.18    | 10.89   |          |
| Multi-hinge [19] | 6.22    | 14.62    | 13.35   |          |
| FQ-GAN [43]  | 6.16    | 8.23     | 10.62   |          |
| ADA [16]     | 2.67↑   | 10.06↑   | -       | -        |
| Omni-GAN (one-sided) | 6.98    | 8.28     | 10.99   |          |
| Omni-GAN     | 5.52    | 8.14     | 13.51   |          |

Table 1: FID and IS on CIFAR10 and CIFAR100. Note that ADA used a larger network than ours (512 vs. 256, feature maps for all layers). † indicates quoted from the paper.

Figure 6: FID and IS on ImageNet 32 × 32. Omni-GAN converges faster in terms of FID and shows an astonishing IS compared to projection-based cGAN.

SPADE\(^ \text{3} \) as our baseline. Hyperparameters are consistent with those of baselines.

4.2. Class-Conditional Image Generation

We first verify the effectiveness of Omni-GAN on the task of class-conditional image generation.

CIFAR10 and CIFAR100. We re-implemented BigGAN, Multi-hinge GAN, FQ-GAN, and used the official evaluation code to monitor the training process. As shown in Table 1, Omni-GAN achieves both superior FID and IS at the same time on CIFAR10 and CIFAR100. However, there exists a trade-off between FID and IS for other methods. For example, although the classification-based cGAN, Multi-hinge GAN, achieves prominent IS on CIFAR10 and CIFAR100, it gets an inferior FID of 14.62 on CIFAR100. On the other hand, FQ-GAN, which employs a projection discriminator, achieves prominent FID scores, but its IS are ordinary on both CIFAR10 and CIFAR100. Another interesting point is that the performance of one-sided Omni-GAN is worse than that of Omni-GAN, but on par with that of BigGAN. This shows that the excellent performance of Omni-GAN comes from the full use of class supervision. We will comprehensively compare Omni-GAN with BigGAN and Multi-hinge GAN in the discussion (refer to Sec. 5.2, 5.3).

Fig. 5 shows the curves of evaluation scores over the course of training. Obviously, Multi-hinge GAN suffers early collapse on CIFAR100, but not on CIFAR10. We think the reason may be that CIFAR10 has fewer images per class than CIFAR10 (i.e., 500 vs. 5000), in which case the discriminator is more likely to overfit the training data. We will discuss using weight decay to solve this early collapse problem of Multi-hinge GAN in Sec. 5.3. Fig. 5 also shows that Omni-GAN has achieved stable and superior performance on FID and IS at the same time. Considering its simplicity (just changing the loss function of the discriminator), we think Omni-GAN has a potential to be applied in other fields (e.g., super-resolution, image-to-image translation).

ImageNet. ImageNet [7] is a large dataset with 1000 number of classes and approximate 1.2M training data. We downsample the training data to resolution of 32 × 32 and train GAN models for 200 epochs on all the training data. The network architecture remains the same as that of BigGAN. In Fig. 6 we compare Omni-GAN and projection-based cGAN (BigGAN). Omni-GAN, which belongs to classification-based cGANs, once again demonstrates a superior IS compared to the projection-based cGAN. Nevertheless, the FID score of Omni-GAN seems to be on par with that of projection-based cGAN.

4.3. Semantic Image Synthesis

Omni-loss can be easily extended to a fully convolutional discriminator. We show its effectiveness on semantic im-

\(^3\)https://github.com/NVlabs/SPADE
Table 2: Semantic image synthesis using SPADE. Replacing the GAN used by SPADE with Omni-GAN can improve the quality of synthesized images.

|       | road | sidewalk | building | wall | fence | pole | traffic light | traffic sign | vegetation | terrain |
|-------|------|----------|----------|------|-------|------|---------------|--------------|-------------|---------|
| SPADE | 97.44 | 79.89 | 87.86 | 50.57 | 47.21 | 35.90 | 38.97 | 44.67 | 88.15 | 66.14 |
| sky   | 91.61 | 62.27 | 38.67 | 88.68 | 64.96 | 70.17 | 41.42 | 28.58 | 58.86 | 62.21 |

|       | road | sidewalk | building | wall | fence | pole | traffic light | traffic sign | vegetation | terrain |
|-------|------|----------|----------|------|-------|------|---------------|--------------|-------------|---------|
| + Omni-GAN | 97.57 | 81.62 | 88.58 | 53.39 | 50.47 | 35.88 | 41.08 | 46.75 | 89.31 | 67.00 |
| sky   | 92.14 | 63.97 | 41.99 | 89.91 | 71.06 | 74.27 | 56.16 | 33.99 | 61.23 | 65.07 |

Figure 7: Gradients of the omni-loss. (a) Gradients w.r.t. \( s^{(n)} \) and \( s^{(p)} \) are independent. (b) Gradients w.r.t. \( s_k^{(p)} \), \( \{k = 0, 1, \ldots \} \), are automatically balanced. Please see the text in Sec. 5.1 for details. This figure is inspired by [36].

age synthesis which is an image-to-image task. We use Cityscapes dataset [5] as a testbed, and train models on the training set with size of 2,975. The images are resized to 256 × 512. We use SPADE [28] method as our baseline and replace its loss of the discriminator with omni-loss to derive our method. Models are evaluated by the mIoU of the generated images on the test set with 500 images. We use a pre-trained DRN-D-105 [41] as the segmentation model for the sake of evaluation. As shown in Table 2, OmniGAN improves the mIoU score of SPADE from 62.21 to 65.07, substantiating that the synthesized images possess more semantic information. We believe that the improvement comes from the improved ability of the discriminator in distinguishing different classes, so that the generator receives better guidance and thus produces images with richer semantic information.

4.4. Cross-domain Generation

Omni-loss is essentially a multi-label classification loss [35] and naturally supports classification with multiple positive labels. We have verified the setting with two positive labels above (classification and reality). To further verify the ability of omni-loss to multi-label classification, we constructed a mixed dataset containing images of digits from two distinct domains, namely MNIST [21] of handwritten digits and SVHN [26] of house numbers in Google Street View images. In this setting, the discriminator needs to predict three attributes, class (recognizing digits), domain, and reality. Due to the limited space, please refer to Appendix B for more experimental details.

5. Discussion

5.1. Gradient Analysis

The gradients of omni-loss have two properties: on one hand, the gradients w.r.t. \( s^{(n)} \) and \( s^{(p)} \) are independent; on the other hand, the gradients w.r.t. \( s_k^{(p)} \) (or \( s_k^{(n)} \), \( \{k = 0, 1, \ldots \} \), are automatically balanced. To illustrate these properties, we visualize the gradients of omni-loss. Fig. 7a shows a case that only contains one \( s^{(n)} \) and one \( s^{(p)} \). A, B, and C have the same \( s^{(p)} \), which is 0, but different \( s^{(n)} \) (i.e., 4, 0, −4, respectively). As a result, the gradients w.r.t. \( s^{(p)} \) at these three points are the same (i.e., 0.5). Nevertheless, the gradients w.r.t. \( s^{(n)} \) at these three points are different. For example, the gradient w.r.t. \( s^{(n)} \) at A is largest (equal to 0.98). The reason for this is that the objective of omni-loss is to minimize \( s^{(n)} \). Thus the larger the \( s^{(n)} \), the larger the gradient w.r.t. \( s^{(n)} \).

In Fig. 7b, we show the ability of omni-loss to automatically balance gradients. We consider a case with only two positive labels, namely \( s_0^{(p)} \) and \( s_1^{(p)} \). Note that this case is the same as that of one-sided Omni-GAN. We can observe that for A, its \( s_0^{(p)} \) is smaller than \( s_1^{(p)} \) (i.e., −2 vs. 0). As a result, the gradients w.r.t. \( s_0^{(p)} \) is larger than that w.r.t.
1.0

\[ s_1^{(p)} \] (i.e., 0.79 vs. 0.11), meaning that the omni-loss try to increase \( s_0^{(p)} \) with higher superiority. A similar analysis applies to \( C \) as well. For \( B \), since \( s_0^{(p)} \) and \( s_1^{(p)} \) are equal, the gradients of them are also equal (0.33).

5.2. Comparison with Projection-based GAN

We have shown in Sec. 3.1 that Omni-GAN can be degraded into one-sided Omni-GAN. In this section, we compare one-sided Omni-GAN and projection-based GAN (in particular, BigGAN) on CIFAR100. As shown in Fig. 8, obviously, the IS of one-sided Omni-GAN is worse than that of Omni-GAN, but is comparable with that of projection-based GAN. The reason is that Omni-GAN makes full use of class supervision. However, both one-sided Omni-GAN and the projection-based GAN work in a weaker supervision manner. The same phenomenon still exists on CIFAR10 (refer to Appendix C).

Another interesting phenomenon is that one-sided Omni-GAN collapsed later than the projection-based GAN. In the experiments, we doubled the training time to observe when one-sided Omni-GAN collapses. Fig. 8 shows that one-sided Omni-GAN commences collapsing at a time when about 40M real images is shown to the discriminator, the number which is twice than that of projection-based GAN (about 20M). Note that we did not impose any regularization (e.g., weight decay) on the one-sided Omni-GAN. We think this can be attributed to the characteristic omni-loss owns of balancing gradients automatically (discussed in Sec. 5.1).

5.3. Comparison with Multi-hinge GAN

Multi-hinge GAN belongs to classification-based cGANs, and also suffers from the early collapse issue. In this section, we study whether weight decay is still an effective regularization for Multi-hinge GAN. As shown in Fig. 9, weight decay can indeed make Multi-hinge GAN avoid early collapse. However, the IS of Multi-hinge GAN combined with weight decay is worse than that of Omni-GAN. We also did experiments on CIFAR10 (see Appendix D), and the results also showed the same trend. In addition, considering that Omni-GAN is more versatile than Multi-hinge GAN (e.g., Omni-GAN supports multiple positive labels, while Multi-hinge GAN only supports one positive label), we recommend considering Omni-GAN first when choosing cGANs.

5.4. How to Set the Weight Decay?

We did a grid search on the weight decay and found that its value is related to the size of the training dataset. For CIFAR100, there are only 500 images per class, and the weight decay is set to 0.0005. For CIFAR10, there are 5000 images per class, and the weight decay is set to 0.0001. For ImageNet, it is a large dataset with a considerable number of training data (approximately 1.2M). The weight decay is set to 0.0001. The conclusion is that the smaller the dataset, the higher the risk of over-fitting for the discriminator. Then weight decay should be larger.

5.5. Weight Decay for Generator

We found empirically that applying weight decay also to the generator can make training more stable. As shown in Fig. 10, although only applying weight decay to the discriminator can avoid the risk of collapse earlier, the IS has a trend of gradually decreasing as the training progresses. Fortunately, applying weight decay (set to be 0.001 in our experiments) to the generator can solve this problem. This phenomenon seems to indicate that the generator also has an over-fitting problem.

6. Conclusion

This paper presents an elegant and practical solution to training effective conditional GAN models. The key discovery is that strong supervision can largely improve the upper-bound of image generation quality, but it also makes the model prone to over-fitting. We design the Omni-GAN algorithm that equips the classification-based loss with regularization (in particular, weight decay) to alleviate over-fitting. Our algorithm achieves notable accuracy gains in a few scenarios. Our research implies that there may be more “secrets” in optimizing cGAN models. We look forward to applying the proposed algorithm to more scenarios and investigating further properties to improve cGAN.
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A. FID Results of GANs and cGANs on CIFAR100

We compared the IS of unconditional GANs and conditional GANs (cGANs) in Fig. 1 (in the paper). Their corresponding FID curves are shown in Fig. 11. As can be seen, the unconditional GAN, namely StyleGAN, is inferior to cGANs. Among the cGANs, both BigGAN and Multi-hinge GAN suffer from mode collapse. Omni-GAN not only achieves superior FID, but also enjoys a safe optimization process.

B. Multi-label Discriminator

We constructed a mixed cross-domain datasets by merging two datasets, MNIST and SVHN, which consist of images of digits from different domains. Some example images from the datasets are shown in Fig. 12. Let us take images of MNIST as an example, and show how to set the loss of the discriminator. As for SVHN, the case is analogous. Suppose $x_{\text{real}}$ is an image sampled from MNIST, we set the multi-label vector for $x_{\text{real}}$ as

$$y_{\text{real}} = [0, \ldots, 1_G, \ldots, 0, 1_{\text{mnist}}, 0, 1_{\text{real}}, 0],$$  \hspace{1cm} (16)

where 0 means the corresponding score belongs to the negative set, and 1 to the positive set. As can be seen, $y_{\text{real}}$ possesses three positive labels. The multi-label vector for $x_{\text{fake}}$ is then given by

$$y_{\text{fake}} = [0, \ldots, 0, 0, 0, 0, 1_{\text{fake}}],$$  \hspace{1cm} (17)

which is a one-hot vector with the last element being 1. The discriminator loss is the same as that defined in the paper (Eq. (10)).

For generator, its goal is to cheat the discriminator. We thus let the multi-label vector for $x_{\text{fake}}$ be

$$y_{\text{fake}}^{(G)} = [0, \ldots, 1_G, \ldots, 0, 1_{\text{mnist}}, 0, 1_{\text{real}}, 0],$$  \hspace{1cm} (18)

where $1_G$ is 1 if its index in the vector is equal to the label adopted by the generator to generate $x_{\text{fake}}$, otherwise 0. The generator loss is the same as that defined in the paper (Eq. (12)).

We experimentally found that this multi-label discriminator can indeed instruct the generator to generate images from different domains. Some generated images are shown in Fig. 13. We must emphasize that this is only a preliminary experiment to verify the function of the multi-label discriminator. We think that the multi-label discriminator have a potential to be employed in other tasks in the future, such as

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Figure 11: FID of unconditional GANs and conditional GANs (cGANs) on CIFAR100

Figure 12: Real images sampled from the dataset.

Figure 13: Images generated by a generator which is guided by a multi-label discriminator.
as translation between images in different domains, domain adaptation, etc.

C. Comparison of One-sided Omni-GAN and Projection-based GAN on CIFAR10

We provide the results of one-sided Omni-GAN and projection-based GAN (in particular, BigGAN) on CIFAR10. As shown in Fig. 14, one-sided Omni-GAN is comparable to the projection-based GAN in terms of both FID and IS. The reason is that one-sided Omni-GAN utilizes class supervision in the same way as projection-based GAN. However, both one-sided Omni-GAN and projection-based GAN are inferior to Omni-GAN. Because the only difference between one-sided Omni-GAN and Omni-GAN is whether the supervision is fully utilized, we can easily conclude that the superiority of Omni-GAN lies in the full use of supervision.

D. Combining Multi-hinge GAN with Weight Decay

Figure 15: FID on CIFAR100. Combining Multi-hinge GAN with weight decay can avoid collapsing earlier.

We found that weight decay is still effective for Multi-hinge GAN. Fig. 15 shows the FID curves on CIFAR100. Original Multi-hinge GAN suffers a severe early collapse issue because it employs strong class supervision. After equipped with weight decay, Multi-hinge GAN enjoys a safe optimization and its FID is even comparable to that of Omni-GAN.

Multi-hinge GAN combined with weight decay does not always perform well. The results on CIFAR10 are shown in Fig. 16. To our surprise, weight decay deteriorates Multi-hinge GAN in terms of both FID and IS. The reason for this is unknown. On the other hand, Omni-GAN, employing weight decay by default, achieves superior performance. In addition, Omni-loss is more flexible than multi-hinge loss. For example, it can be easily degraded to a projection-based cGAN, and supports multi-label classification. As a result, we suggest first considering using Omni-GAN when choosing cGAN models.

E. Applying Weight Decay to the Generator

Figure 17: FID curves with or without weight decay for the generator. Experiments are conducted on CIFAR100.

In the paper, we showed that applying weight decay to the generator can make the training process more stable. We provide the FID curves in Fig. 17. It can be seen that applying weight decay to the generator can slightly improve performance in terms of FID. To sum up, applying weight decay to the discriminator can avoid collapse during training. Applying weight decay to the generator at the same
time can improve the performance of the generation.

F. Additional Results

F.1. Generated Images on CIFAR and ImageNet

In Fig. 18, 19 and 20, we show generated images from Omni-GAN on CIFAR10, CIFAR100, and ImageNet datasets respectively. Due to limited space, we only show images of some categories on CIFAR100 and ImageNet.

F.2. Results of Semantic Image Synthesis

In Fig. 21, we show several results of Omni-GAN as well as those of SPADE for semantic image synthesis. The label maps and the ground truth images are from the first ten items in the test set of Cityscapes dataset, without cherry-picking.
Figure 20: Randomly generated image by Omni-GAN for ImageNet.
Figure 21: Results of semantic image synthesis on Cityscapes.