An Empirical Study of the Effects of Sample-Mixing Methods for Efficient Training of Generative Adversarial Networks

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Abstract

It is well-known that training of generative adversarial networks (GANs) requires huge iterations before the generator’s providing good-quality samples. Although there are several studies to tackle this problem, there is still no universal solution. In this paper, we investigated the effect of sample mixing methods, that is, Mixup, CutMix, and newly proposed Smoothed Regional Mix (SRMix), to alleviate this problem. The sample-mixing methods are known to enhance the accuracy and robustness in the wide range of classification problems, and can naturally be applicable to GANs because the role of the discriminator can be interpreted as the classification between real and fake samples. We also proposed a new formalism applying the sample-mixing methods to GANs with the saturated losses which do not have a clear “label” of real and fake. We performed a vast amount of numerical experiments using LSUN and CelebA datasets. The results showed that Mixup and SRMix improved the quality of the generated images in terms of FID in most cases, in particular, SRMix showed the best improvement in most cases. Our analysis indicates that the mixed-samples can provide different properties from the vanilla fake samples, and the mixing pattern strongly affects the decision of the discriminators. The generated images of Mixup have good high-level feature but low-level feature is not so impressive. On the other hand, CutMix showed the opposite tendency. Our SRMix showed the middle tendency, that is, showed good high and low level features. We believe that our finding provides a new perspective to accelerate the GANs convergence and improve the quality of generated samples.

1 INTRODUCTION

Generative adversarial networks (GANs) are considered as one of the most promising frameworks for data-synthesis. Although there are some variations, the training of GANs is an adversarial game between two neural networks: one is a generator which tries to synthesize realistic sample (fake samples), and the other is a discriminator which tries to distinguish between real and fake samples.

Despite its promising properties of GANs, it is also known that GANs training is difficult. To make matters worse, it demands huge iterations before providing good-quality samples. Concerning the difficulty of GANs training, a considerable amount of effort has been conducted on finding its origin and several regularization techniques have been found effective for stabilization. In particular, one of the most accepted findings is that training a good discriminator is a key for a stable and fast training of GANs. In spite of those research activities, this is still an open problem for the GANs research community.

In this paper, we investigated the effect of sample mixing methods, that is, Mixup, CutMix, and newly proposed Smoothed Regional Mix (SRMix) to alleviate the above problem. The sample-mixing methods enhance the accuracy and robustness in the wide range of classification problems. This means that the sample-mixing methods can be expected to effective also for GANs because the role of the discriminator can be interpreted as the classification between real and fake samples. We proposed a new formalism applying the sample-mixing methods to GANs training, in particular, GANs with modern saturated losses such as the Wasserstein loss and Hinge loss which do not have a clear “label” of real and fake samples. In addition, our simple implementation allows us to combine it with any regularization methods, such as gradient penalty, spectral-normalization, and consistency-regularization. We performed a vast amount of numerical experiments using LSUN and CelebA datasets, and analyzed the effects of sample-mixing methods on GANs training.

In summary, our contributions are as follows:

• We proposed a new sample-mixing method: Smoothed Regional Mix (SRMix). We also proposed a new...
formalism of applying the sample-mixing methods to GANs with saturated loss functions. (Section\textsuperscript{3}).

- We performed comprehensive numerical experiments, and found that Mixup and SRMix were effective also for GANs. (Section\textsuperscript{4}).
- We analyzed the resulting fake samples, and provided the insights of the effects of each sample-mixing method (Section\textsuperscript{6}).

2 Related Work

GANs Generative adversarial networks (GANs)\textsuperscript{5} are considered as one of the most promising frameworks for data-synthesis. One of the most attractive properties of GANs is their flexibility; they allow us to synthesize nearly any kind type of the data, such as image generation\textsuperscript{12,34,4,13}, super-resolution of images\textsuperscript{18}, text\textsuperscript{10,31}, voice\textsuperscript{9}, and even text-to-image\textsuperscript{26,28}. Concerning the difficulty of GANs training, although this is still a very hot research topic, there are several techniques that are known very effective for stabilization, such as the gradient penalty\textsuperscript{6}, and spectral-normalization\textsuperscript{22}. Recently it was found that the consistency-regularization\textsuperscript{28,17}, which is one of the most popular methods for semi-supervised learning, is very effective for the stabilization of GANs training\textsuperscript{35}. Our paper followed this line, and analyzed another popular semi-supervised methods: Mixup and its variants.

Mixup Mixup\textsuperscript{33} is a regularization method for DNN classifiers by creating virtual samples and labels in the vicinity of the distributions of the mixed data\textsuperscript{7}. This method is known effective for many problems of DNN, such as memorization, sensitivity to adversarial examples, and supporting semi-supervised learning\textsuperscript{3}.\textsuperscript{29} found that interpolating hidden states can result in a better representation. In spite of this success, Mixup is also known to introduce unnatural artifacts because of the global mixing, leading sub-optimal performance of the classifiers. CutMix\textsuperscript{32} is a method which alleviate this problem by creating a new sample by regionally mixing two samples. The authors found that this regional mixing encourages DNN classifiers to focus on discriminative local parts, resulting in consistent performance gains. Note that in\textsuperscript{33}, the authors tried to apply Mixup to the original GAN loss (non-saturated loss), and reported the training were stabilized. However, the authors reported neither Inception nor FID score. In addition, we also emphasize that the author’s method cannot directly be applied to the saturated losses because they do not have a clear "label" of real and fake samples which is one of the key components of Mixup. In this paper, we applied the sample-mixing methods for various saturated loss functions, and analyzed their effects.

Algorithm 1 Algorithm of GANs training with mixed-samples

\begin{itemize}
  \item Input generator and discriminator parameters $\theta_G$, $\theta_D$, ladder ratio $r$, Adam hyper-parameters $\eta$, $\beta_1$, $\beta_2$, batch size $M$, number of discriminator iterations per generator iteration $n_{crit}$
  \item 1: for number of training iterations do
  \item 2: \hspace{0.5cm} for $t = 1$ to $n_{crit}$ do
  \item 3: \hspace{1cm} for $i = 1$ to $M$ do
  \item 4: \hspace{1.5cm} Sample real data $x \sim p_{data}(x)$, latent variable $z \sim p(z)$.
  \item 5: \hspace{1.5cm} if $i \leq rM$ then
  \item 6: \hspace{2cm} $\tilde{x} \leftarrow$ mixed-sample
  \item 7: \hspace{1.5cm} else
  \item 8: \hspace{2cm} $\tilde{x} \leftarrow G(z)$
  \item 9: \hspace{1cm} end if
  \item 10: \hspace{1cm} $L^{D(i)} \leftarrow D(\tilde{x}) - D(x)$
  \item 11: \hspace{1cm} end for
  \item 12: \hspace{0.5cm} $\theta_D \leftarrow \text{Adam}\left(\sum_{i=1}^{M} L^{D(i)}, \eta, \beta_1, \beta_2\right)$
  \item 13: \hspace{1cm} end for
  \item 14: \hspace{0.5cm} Sample a batch of latent variables $\{z^{(i)}\}_{i=1}^{M} \sim p(z)$
  \item 15: \hspace{1cm} $\theta_G \leftarrow \text{Adam}\left(\sum_{i=1}^{M} (-D(G(z))), \eta, \beta_1, \beta_2\right)$
  \item 16: \hspace{1cm} end for
\end{itemize}

3 Methods

In this section, we provide a detailed explanation of our new formalism to combine sample-mixing methods to GANs with saturated loss functions effectively. As is well-known, Mixup assumes to mix both samples and labels which is necessary to encourage classifiers to learn the mixed-samples as located in the vicinity of the distributions of the mixed data. However, GANs with the saturated loss functions do not have "label" of real and fake samples, so that Mixup cannot directly be applied in this case. It is also non-trivial how to provide the mixed samples to the discriminator without interfering the discriminator’s learning of the fake samples. To solve these problems, we proposed the following new formalism.

In our formalism, we proposed not to use "label" mixing because of the absent of the label in the case of the saturated loss functions\textsuperscript{1}. Instead, our formalism regards the mixed-sample as a new kind of fake samples whose distribution is located in the vicinity of the distributions of real and fake samples but not necessarily between them. In the case of the standard procedure for stable GANs training, it is common to construct different mini-batches for real and fake samples. In our formalism, a certain amount of fake samples were replaced by the mixed-samples at every it-

\footnote{Note that it is possible to use the generator’s output of real and fake samples as a pseudo-label. However, our numerical experiments using the pseudo-label did not show any improvement of FID score.}
Table 1. A summary of training setups in Section 5. NM means the normalization of the discriminators. LN means the layer normalization, and SN the spectral normalization. GP means the gradient penalty. CR means the consistency regularization.

| Names  | Model         | Loss        | NM       | Regularization |
|--------|---------------|-------------|----------|----------------|
| Case 1 | DCGAN         | Hinge       | LN       | CR & GP        |
| Case 2 | DCGAN         | Hinge       | SN       | CR             |
| Case 3 | ResNet        | Hinge       | LN & SN  | CR & GP        |
| Case 4 | StyleGAN2     | vanilla     |          |                |

The creation of a mixed samples by those method can formally be written as:

\[ \tilde{x} = M \odot x_i + (1 - M) \odot x_j, \] (1)

where \( x_i \) and \( x_j \) are two sample data, \( M \in [0, 1]^{W \times H} \) is a mask, and \( \odot \) is element-wise multiplication. In the case of Mixup, the mask \( M \) is constant for all the images, and its value (described as \( \lambda \) in the paper [33]) is sampled from the Beta distribution as \( \lambda \sim \text{Beta}(\alpha, \alpha) \), for \( \alpha \in (0, \infty) \). In the case of CutMix, the mask \( M \) has a rectangular non-zero (unity) region whose box coordinates \( (r_x, r_y, r_w, r_h) \) are determined by uniform sampling. In the case of SRMix, we regionally mix two samples as CutMix but allows a transient region by connecting them by a smooth function such as the hyperbolic-tangent function: the mask \( M \) can be written as:

\[ M \equiv \frac{1}{2} [1 + \sigma \tanh((x^{t} - x^{0})/\Delta x^{t})], \] (2)

where \( \sigma \) is either \( \pm 1 \) determined randomly, and \( x^{t} \) denotes one of the pixel coordinate (either horizontal or vertical direction) whose direction is randomly determined for each sample. \( x^{0} \) is the central coordinate of the transient region, and \( \Delta x^{t} \) is the width of the transient region. Note that SRMix not only simulates CutMix but Mixup by introducing the transient region. In the following experiments, \( \alpha \) of the Beta distribution is set to unity, that is, uniform distribution of sampling is assumed; \( x^{0} \) is chosen from 1/8 to 7/8 of the image coordinate, and \( \Delta x^{t} \) ranges from 2 pixels to 1/16 of the resolution of the image.

4 Experiments

In this section, we provided the numerical results of our experiments to investigate the effects of the sample-mixing methods on GANs training. We performed the experiments using several GAN architectures and loss functions on five datasets. All the scores were measured by Frechet Inception Distance (FID) [8]. In particular, we used all the training data as the reference of real samples when calculating FIDs, and compared them with 10k fake samples. In all the tests, we performed five-training and obtained averages and standard deviations to reduce statistical fluctuations. The training was performed using PyTorch 1.3 for Case 1-3 and Pytorch 1.6 for Case 4 [24].

Datasets We evaluated our method using five datasets, CELEBA-HQ-128 (CelebA) [21], LSUN’s training data of bedroom, church_outdoor, tower, and bridge [30]. On all the datasets, we performed Resize, CenterCrop, and Normalize using PyTorch APIs in this order. The resolutions are 128 \times 128 on CelebA in Section 5 and 64 \times 64 on the other cases.

Models and Loss functions As model architectures of the generator and discriminator, we used DCGAN [25] and the ResNet-like structure proposed in [6]. On the generator, batch normalization [11] was used. On the discriminator, either spectral normalization or layer normalization [2], or both, was used. In the Case 4, we used StyleGAN2 [14]. The summary of the models, loss functions, normalization of the discriminator, and regularization are listed in Table I. For simplicity, we used unconditional GANs for all the cases.

Training For the training, we set the batch size 64 in the Cases 1-3, and 4 in the Case 4. The training was stopped after 100k iterations in Cases 1-3 and 150k iterations in Case 4. Note that the number of iterations was relatively small. This is because the deformation of image contents created by sample mixing can be expected harmful to discriminators training in the final-phase, which will be discussed in Sections 5 and 6. The optimization was performed using Adam [15] with parameters \((\beta_1, \beta_2) = (0.01, 0.999)\). The learning rate was set to \( \eta = 10^{-3} \) in all the generators and the discriminator in Section 5. The number of discriminator iterations per generator iteration was set as \( n_{\text{crit}} = 2 \).

2 Recently a similar method, SmoothMix [19], was proposed which is CutMix with soft edge for classification problems. We found that our SRMix corresponds to a simpler version of this methods.

3 To perform the experiment for StyleGAN2, we used an implementation provided in https://github.com/lucidrains/stylegan2-pytorch whose tag is 1.5.6, with its vanilla setting and parameters. We really appreciate the authors of the repository.

4 In the cases 1 and 3 of Section 5, gradient penalty was used for every 5 iterations, which we found was enough for improving FID scores and allowed us a more efficient training.
Concerning the consistency-regularization, the augmentation is a combination of randomly flipping the image horizontally and randomly shifting the image by 4 pixels following [5]. The coefficient of consistency regularization was set as unity in all the experiments in Section 5.

5 Results

In this section, we present the results of the experiments using Mixup, CutMix, and SRMix. The mixed samples occupied 25% in the Cases 1 and 2, and 15% in the Cases 3 and 4 in one mini-batch, respectively. The results were listed in Table II which showed that adding mixed samples mostly improved FID scores comparing with vanilla training. In particular, they indicated that SRMix worked well in most cases; On the other hand, CutMix failed to improve FID in most cases. To understand this tendency, in top-panels in Figure 1, we plotted the distributions of the discriminator’s evaluation of the quality of real, fake, and mixed samples in the Case 1 using LSUN bedroom dataset where Mixup and SRMix showed improvement of their FID scores. It showed that the location of the mixed sample distribution correlated with FID scores. In the cases of Mixup and SRMix, the created mixed samples are distributed around fake samples, in particular, samples created by SRMix are distributed much worse than fake samples. On the contrary, the mixed samples by CutMix are distributed much worse than fake samples. On the other hand, bottom-panels in Figure 1 is the plot of the sample distributions of real, fake, and mixed samples in the case of Case 2 using LSUN bridge where all the methods failed to improve their FID scores. It showed that the mixed sample distributions of all the cases failed to produce better samples than the fake ones, indicating the importance of the better mixed samples than fake ones. The above results indicate that the FID scores became better when the mixed samples are distributed between real and fake samples. Note that this is the intended behavior of sample-mixing methods but interestingly this did not always work well. In Section 6, we analyze the reason of this behavior more deeply.

Table III showed the development of FID scores in the Case 3 using LSUN bedroom dataset. It showed that the sample-mixing did not always work in the early phase. Besides, SRMix worked well around the middle-phase (50k to 75k iterations) but showed a poor performance in the late phase (100k). We consider that this is because the samples created by SRMix was fruitful for the discriminator around the middle-phase but became too easy at the late-phase because of the ability of ResNets's capturing the high-level feature of images which can detect unnatural artifacts introduced by the sample-mixing.

In the Case 4, we performed experiments using StyleGAN2 which is known as one of the most successful GANs model at present, allowing us to generate high-resolution images. Table IV showed the average and minimum FID scores, using CelebA bedroom dataset. Similar to the Case 3, it also indicated that the sample-mixing did not work well in this case. We consider that this is due to the ability of StyleGAN2 capturing both the low and high-level feature of images. However, we also noted that SRMix resulted in the best FID value in terms of the minimum value of the obtained FID in 5 trials. This indicates that sample-mixing methods can be beneficial even for modern GAN models capable of capturing high-level features, but needs a more sophisticated methods to control the strength of the fluctuation from sample-mixings, such as adaptively changing sample-mixing samples ratio in fake data.

6 Analysis

In this section, we analyzed the effects of mixed-samples on the discriminator’s decisions. Figure 2 is the generated images by sample-mixing (Top) and the discriminators’ outputs (Bottom). We found that the discriminator of CutMix properly detected the region where the fake sample is cut into the real sample (right-hand side of the image). On the contrary, the discriminator of SRMix did not react to the transient region (middle of the image). This indicates

Table 2. FID score of the GAN training with the help of sample mixing.

| Case   | Type   | Bedroom | Church | Bridge | Tower | CelebA |
|--------|--------|---------|--------|--------|-------|--------|
| Case 1 | vanilla| 22.2 ± 4.2 | 15.5 ± 2.3 | 22.1 ± 1.5 | 15.1 ± 2.2 | 11.5 ± 0.7 |
|        | Mixup  | 20.3 ± 3.4 | 14.8 ± 2.2 | 23.4 ± 1.8 | 16.5 ± 2.1 | 11.6 ± 0.9 |
|        | CutMix | 22.2 ± 1.2 | 13.6 ± 0.6 | 25.6 ± 5.2 | 16.6 ± 1.5 | 12.4 ± 0.7 |
|        | SRMix  | 19.5 ± 1.6 | 13.4 ± 1.2 | 21.2 ± 2.9 | 15.0 ± 1.3 | 12.2 ± 0.6 |
| Case 2 | vanilla| 33.9 ± 1.8 | 20.4 ± 2.1 | 27.0 ± 1.7 | 21.8 ± 2.5 | 15.5 ± 0.7 |
|        | Mixup  | 30.7 ± 3.7 | 17.8 ± 0.5 | 28.6 ± 1.3 | 20.8 ± 1.4 | 14.1 ± 0.6 |
|        | CutMix | 37.8 ± 1.2 | 24.2 ± 1.3 | 36.8 ± 3.2 | 26.6 ± 1.5 | 18.0 ± 0.8 |
|        | SRMix  | 27.0 ± 2.5 | 18.4 ± 1.3 | 27.1 ± 1.7 | 19.7 ± 2.2 | 13.8 ± 1.0 |

Note that the discriminator’s outputs were normalized to range from 0 (black) to unity (white) by the post-process.
Table 3. Development of FID scores of the GAN training in terms of the iteration numbers in the Cases 3 using LSUN bedroom dataset.

| Type | 1k    | 10k   | 25k   | 50k   | 75k   | 100k  |
|------|-------|-------|-------|-------|-------|-------|
| vanilla | 210.6 ± 26 | 70.7 ± 45.7 | 22.5 ± 4.6 | 13.1 ± 2.7 | 12.0 ± 1.7 | 9.4 ± 1.2 |
| Mixup  | 210.0 ± 24 | 80.0 ± 53.8 | 25.5 ± 10.5 | 13.5 ± 2.7 | 10.3 ± 2.3 | 8.7 ± 1.2 |
| CutMix | 214.3 ± 21 | 59.4 ± 15.6 | 24.5 ± 7.2 | 13.2 ± 3.2 | 11.2 ± 2.6 | 9.4 ± 0.6 |
| SRMix  | 206.1 ± 18 | 76.0 ± 42.5 | 22.8 ± 4.2 | 11.6 ± 1.7 | 9.4 ± 1.0 | 9.7 ± 1.0 |

Figure 1. Distribution functions of real, fake, and mixed samples created by Mixup, CutMix, and SRMix in Case 2. Top panels: LSUN bedroom dataset. Bottom panels: LSUN bridge dataset. The blue, orange, and green histograms corresponds with real, fake, and mixed samples' discriminator evaluation, respectively.

Table 4. The average and minimum value of the FID scores of the GAN training in the Cases 4 using CelebA dataset.

| Case    | average | minimum |
|---------|---------|---------|
| vanilla | 20.7 ± 1.2 | 19.4    |
| Mixup   | 22.0 ± 2.4 | 19.9    |
| CutMix  | 23.6 ± 1.4 | 21.6    |
| SRMix   | 22.6 ± 2.5 | 19.1    |

that the discriminator of CutMix used the strong edge of the boundary region as a clue to find sample-mixing samples. This was also be indicated from the left-hand side of the discriminator’s output where the discriminator’s judge becomes white, meaning real sample, in almost all the region, showing that the discriminator neglects other image features to judge if the sample is real or fake. Concerning the Mixup (left panels), it showed that the discriminator paid attention to various regions because of the global linear interpolation. However, it failed to give a penalty on the unnatural regions resulting from the linear interpolation of two images, which does not occur in the real images. On the other hand, SRMix allowed the discriminator to learn from the true real and fake samples avoiding appearance of the strong edge, which makes SRMix as a better provider of samples between real and fake in most cases.

Figure 3 plots the true and fake images generated by the generators trained using Mixup, SRMix, and CutMix. This indicates that Mixup encouraged the generator to produce images with good high-level information, but the low-level information (e.g. form of bed) is relatively poor. On the other hand, CutMix encouraged the generator to produce images with good low-level information, but the high-level
Figure 2. Top panels are the examples of Mixed-samples generated by Mixup (left), SRMix (middle), and CutMix (right). The bottom panels are the corresponding discriminator’s outputs in \(4 \times 4\) regions (the darker, the worse). SRMix image (middle-top) has a transient region around the middle of the image. CutMix image (right-top) has a region in the right-hand side of the image where fake sample is cutting-in.
Figure 3. Comparison of true and fake images generated by the generators trained using Mixup, SRMix, and CutMix.
information is poor. SRMix showed the intermediate features of the two methods. We consider that those tendency played an important role for a better FID score of Mixup and SRMix because FID measures the distance of high-level information between real and fake images.

7 Discussion And Conclusion

In section 4 we performed the numerical experiments using mixed samples to GANs training. In most cases, we observed the improvement of the FID score, in particular, in the case of SRMix. However, the improvement of the FID scores was relatively unstable and sometimes became even worse than vanilla training. One of the reasons for this was indicated in Figure 1 which showed that the produced samples were not always located between real and fake samples but located far left of fake samples, indicating too easy for discriminators to judge as fake samples. We consider that this can be partly due to the deformation of the contents in the resulting samples, for example, human faces and buildings, which can be too easy for a well-trained discriminator to detect. This means that we may have to stop using mixed-samples in the later phase of the GANs training since this is an intrinsic problem of the sample-mixing method.

In conclusion, the sample-mixing methods were indicated to be fruitful even for an effective GANs training from our numerical experiments. On the other hand, it was also shown that our proposed methods to create mixed-samples did not always work, in particular, when the samples failed to be located between real and fake data in terms of the discriminator’s evaluation. In order for a better GAN training, it is crucial to find a method to create good samples more stably than Mixup, CutMix, and SRMix, and we will tackle it in our future work.

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