FusedProp: Towards Efficient Training of Generative Adversarial Networks

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Abstract

Generative adversarial networks (GANs) are capable of generating strikingly realistic samples but state-of-the-art GANs can be extremely computationally expensive to train. In this paper, we propose the fused propagation (FusedProp) algorithm which can be used to efficiently train the discriminator and the generator of common GANs simultaneously using only one forward and one backward propagation. We show that FusedProp achieves 1.49 times the training speed compared to the conventional training of GANs, although further studies are required to improve its stability. By reporting our preliminary results and open-sourcing our implementation, we hope to accelerate future research on the training of GANs.

1. Introduction

Generative adversarial networks (GANs) have been continually progressing the state-of-the-art in generative modeling of all kinds of data since its invention [4]. Among its many applications, image generation arguably has received the most attention due to its strikingly realistic results [7, 8, 9, 27, 2]. However, the training of these powerful GANs usually takes days to weeks even on high-end multi-GPU/TPU machines, strongly limiting the number of experiments researchers can afford and negatively affecting the fairness and progress of the field.

To mitigate this challenge, existing work mainly relied on two types of acceleration. The first is to use lower numerical precision, e.g., half precision (fp16) instead of single precision (fp32) for training [7, 8, 9, 2]. The second is to adapt GAN’s architecture using e.g., progressive growing [7], simplified normalization [9], shared embedding [21, 2], etc.

In this paper, we aim to accelerate the training procedure of GANs and propose the fused propagation (FusedProp) algorithm, a generalization of the gradient reversal algorithm [3] that can be used to train the discriminator and the generator of common GANs simultaneously using only one forward and one backward propagation. Our algorithm offers 1.49× the training speed compared to the conventional training of GANs and our code is publicly available. Although further studies are required to improve the stability of FusedProp, we hope our preliminary results and open-source implementation of FusedProp can accelerate future research on the training of GANs.

2. Background

The training of a GAN entails the minimax optimization of a two-player game between its discriminator $D$ and its generator $G$ defined as

$$
\max_D \min_G \mathcal{L}_D^R(D(x)) + \mathcal{L}_D^F(D(G(z)))
$$

where $G$ is trained (by maximizing $\mathcal{L}_D^F$) to map the latent variable $z$ from a given (e.g. normal) distribution into $G(z)$ that resembles the real data $x$ such that $D$ can not tell $G(z)$ and $x$ apart even if it is trained (by minimizing $\mathcal{L}_D^R$ and $\mathcal{L}_D^F$) to do so. It is rather common to write the optimization of $D$ and $G$ separately as

$$
\min_D \mathcal{L}_D^R(D(x)) + \mathcal{L}_D^F(D(G(z)))
$$

$$
\min_G \mathcal{L}_G(D(G(z)))
$$

which allows for GAN losses with $\mathcal{L}_G \neq -\mathcal{L}_D^F$ and thus more desirable properties (e.g. stronger gradients using the nonsaturating loss [4], see Table 1 and its references for more details). For simplicity, we also write $\mathcal{L}_D^F$ as $\mathcal{L}_D$ in the rest of the paper.

$$
\theta_D^{i+1} = \theta_D^i - \alpha \frac{\partial \mathcal{L}_D^R(D(x;\theta_D^i)) + \mathcal{L}_D(D(G(z;\theta_G^i);\theta_D^i))}{\partial \theta_D^i}
$$

$$
\theta_G^{i+1} = \begin{cases} 
\theta_G^i - \alpha \frac{\partial \mathcal{L}_G(D(G(z;\theta_G^i);\theta_D^i))}{\partial \theta_G^i} & \text{(SimGD)} \\
\theta_G^i - \alpha \frac{\partial \mathcal{L}_G(D(G(z;\theta_G^i);\theta_D^{i+1}))}{\partial \theta_G^i} & \text{(AltGD)}
\end{cases}
$$

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Figure 1. Conventional vs. fused propagation (FusedProp) and inverted fused propagation (InvFusedProp) training of GANs, where gray arrow indicates forward propagation, colored arrow indicates backward propagation and dashed arrow indicates conditional dependency. $\mathcal{L}_D^R$ is omitted for simplicity.

| Loss          | $\mathcal{L}_D^R$ | $\mathcal{L}_D$ | $\mathcal{L}_G$ | $\lambda$ | $\lambda^{-1}$ |
|---------------|--------------------|-----------------|-----------------|-----------|----------------|
| Minimax [4]   | softplus($-y$)     | softplus($y$)   | $-\text{softplus}(y)$ | $-1$     | $-1$           |
| Nonsaturating [4] | softplus($-y$)     | softplus($y$)   | $-\text{softplus}(y)$ | $-e^{-y}$ | $e^{y}$        |
| Wasserstein [1] | $-y$              | $y$             | $-y$            | $-1$     | $-1$           |
| Least Squares [13] | $(y - 1)^2$        | $y^2$           | $-(y - 1)^2$    | $1 - y^{-1}$ | $y \cdot (y - 1)^{-1}$ |
| Hinge [12, 24] | ReLU($-y + 1$)     | ReLU($y + 1$)   | $-y$            | $\frac{1}{\beta}$ | $-\text{H}(y + 1)$ |

Table 1. Common GAN losses and corresponding gradient scaling factors for FusedProp and InvFusedProp, where $\text{softplus}(x) = \ln(1+e^x)$, ReLU($x$) = max($x, 0$) and $H$ denotes the Heaviside step function.

Although the training of $D$ and $G$ is often described as simultaneous, it is rarely the case in practice. Specifically, instead of updating $\theta_D$ and $\theta_G$ simultaneously using SimGD [14] as defined in Eq. (3), updating them alternatingly using AltGD [14] (often with multiple $\theta_D$ updates per $\theta_G$ update) is much more common, partly due to the stability and convergence concerns about SimGD [23, 15, 14]. However, researchers’ view about SimGD is not unilaterally pessimistic since [19, 6] proved SimGD can lead to stable convergence of GANs as well. Encouraged by the positive results, we seek to accelerate the training of GANs based on the SimGD approach.

Of course, SimGD itself is not more computationally efficient than AltGD if one still needs to compute gradients for $\theta_D$ and $\theta_G$ using two backpropagations. Fortunately, it is known that if $\mathcal{L}_G = \lambda \mathcal{L}_D$ for some constant $\lambda$ (e.g., $\lambda = -1$ as in the minimax loss), the gradient reversal algorithm [3] originally designed for the domain adaptation problem can be used to combine the two backpropagations by inserting a simple function $\text{GR}$ defined as

$$
\text{GR}_\lambda(x) = x
$$

$$
\frac{\partial \text{GR}_\lambda(x)}{\partial x} = \lambda I
$$

between $D$ and $G$. Inspired by the gradient reversal algorithm, we aim to bring its level of efficiency to the training of GANs while supporting a broader set of GAN losses.

3. Algorithm

Although [3] also mentioned the possibility of generalizing the gradient reversal algorithm to arbitrary GAN losses, it is unclear if such generalization can be implemented as efficiently. To this end, we formally derive the fused propagation (FusedProp) algorithm, a generalization of the gradient reversal algorithm for common GAN losses, and outline its implementation in the rest of the section.

The first form of FusedProp closely follows the gradient reversal algorithm, except with a data-dependent gradient
class FusedProp(torch.autograd.Function):
    @staticmethod
    def forward(ctx, Gz):
        return Gz

    @staticmethod
    def backward(ctx, gGz):
        return gGz * _lambda.view(-1, 1, 1, 1)

class InvFusedPropLinear(torch.autograd.Function):
    @staticmethod
    def forward(ctx, x, W, b):
        return gx, gW, gb

    def backward(ctx, gy):
        x, W = ctx.saved_tensors
        return gy.matmul(W) * _lambda_inv.view(-1, 1), W, b

Figure 2. PyTorch example of FusedProp training, where P1–P4 describe the procedure of one iteration and F1–F2 describe the FusedProp steps.

Figure 3. PyTorch example of InvFusedProp-based linear (i.e., fully connected) layer, where I1–I3 describe the InvFusedProp steps. See our code for examples of other types of layers.

and in Fig. 1, one can also obtain $\frac{\partial L_D}{\partial \theta_D}$ during $L_G$ minimization by scaling the “incorrect” gradient $\frac{\partial L_G}{\partial \theta_G}$ by $\lambda^{-1}$. Worth to note, unlike FusedProp which can be trivially done in most deep learning frameworks, InvFusedProp requires additional effort to implement correctly and efficiently.\textsuperscript{5} This is due to the fact that $\lambda^{-1}$ takes different values for different data in a batch, but in most frameworks gradients for parameters (here $\frac{\partial L_G}{\partial \theta_G}$) are only available as already reduced across all data in a batch for performance reasons. Instead, one should pre-scale the gradient by $\lambda^{-1}$ before computing gradients for parameters within each layer of $D$. A PyTorch example of InvFusedProp-based layer is provided in Fig. 3. InvFusedProp is slightly slower than FusedProp as additional scaling operations are needed in all layers of $D$. For GAN losses with valid but different $\lambda$ and $\lambda^{-1}$ (e.g., the nonsaturating and the least squares loss), it is also possible to adaptively switch between the two forms if the numerical accuracy of one is better than the other.\textsuperscript{7}

Both forms of the FusedProp algorithm are exact and efficient implementations of the SimGD-based training of GANs, which bring the conventional time complexity of $O(6T_D + 3T_G)$ down to $O(4T_D + 2T_G)$, where $T_D$ and $T_G$ stand for the time complexities of the forward and backward propagations of $D$ and $G$ respectively.\textsuperscript{8} As $D$ and $G$

\textsuperscript{4}E.g., for convolutional layers, we need to use MKL-DNN or CuDNN subroutines for InvFusedProp to ensure performance.

\textsuperscript{5}This assumes $L^D_\theta$, $L_D$ and $L_G$ are all using the same batch size, and the gradients for parameters and activation within each layer are computed in parallel. If computed in serial, time complexities are $O(8T_D + 4T_G)$ vs. $O(6T_D + 3T_G)$.

\textsuperscript{6}E.g. when using fp16 for training. We do not observe such need using fp32 in our experiments.

\textsuperscript{7}Due to the commutative property of the scalar and (Jacobian) matrix product.
are commonly of similar complexity (i.e. $T_D \approx T_G$). We can expect approximately $1.5 \times$ theoretical speedup by using FusedProp training. SimGD-based training of GANs however is not guaranteed to match the results of the conventional AltGD-based training, thus needs to be experimentally validated too.

4. Experiments

In this paper, we closely follow the setup of [17], i.e. unconditional CIFAR10 image generation using CNN or ResNet-based GANs with nonsaturating or hinge loss to validate the FusedProp algorithm. We perform 5 runs for all configurations and summarize their Inception Scores (IS), Frchet Inception Distances (FID) and speed measured in iterations per second at batch size of 64 for conventional and FusedProp training. For ResNet-based experiments, we first adopt the TTUR [6] learning rate pair used by [27] but find that FusedProp training performs significantly worse than conventional training in this setting. With some manual tuning, we are able to stabilize FusedProp training and eliminate the difference in terms of IS and FID between conventional and FusedProp training. For ResNet-based experiments, we observe sizable speedups using FusedProp training in all settings, ranging from $1.45 \times$ to $1.55 \times$ (overall $1.49 \times$) which match the theoretical analysis.

Other factors that may cause a difference between conventional and FusedProp training are as follows. First, conventional training implicitly uses twice the amount of power iterations in the spectral normalization compared to FusedProp. Second, conventional training uses twice the amount of generated images in each iteration by redrawing $z$ compared to FusedProp. However, we do not observe meaningful changes in the IS and FID when we correct conventional or FusedProp training to match each other in these two regards, implying that the fundamental difference between AltGD and SimGD-based training is the root cause here.\(^{11}\)

5. Discussion

Although our preliminary results indicate that FusedProp is not exactly a drop-in replacement for conventional training of GANs as it may require additional hyperparameter tuning due to SimGD’s different nature, we hope that as more researchers start to realize and utilize its computational efficiency, more research will follow to fundamentally solve the issues of SimGD-based training. At the same time, it will be crucial in our future work to study if existing techniques [14, 26] can be efficiently combined with FusedProp to improve its stability for larger-scale problems.

The FusedProp algorithm also has known limitations, which we list as follows.

1. FusedProp does not provide much speedup if multiple $\theta_D$ updates are required per $\theta_G$ update [1, 5]. We find TTUR an effective replacement in our experiments and recommend using it instead, as also advocated by [27].
2. Gradient penalties on $D$ that involve $G(z)$, including [5, 10] and the R2 penalty [14], are not compatible with FusedProp as their second-order gradients can incorrectly affect $G$. The increasingly popular R1 penalty [14, 8, 9] however is compatible.
3. Most conditional GANs [16, 22, 18] are compatible with FusedProp. However, ones that explicitly use a classification loss in addition to the GAN loss [20] are not compatible as gradients from those two losses become inseparable to be correctly scaled.

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\(^{9}\)Measured in iterations per second at batch size of 64 for $L_D^R$, $L_D$ and $L_G$ using one V100 GPU.

\(^{10}\)Instead of multiple $\theta_D$ updates per $\theta_D$ update as suggested by [11] which we do not currently support.

\(^{11}\)We have also tested SimGD without the FusedProp acceleration and obtained the same results as FusedProp, suggesting this is not due to any flaw in FusedProp.
Table 2. Unconditional CIFAR10 image generation results using conventional (C), FusedProp (F) or InvFusedProp (I) training, nonsaturating (NS) or hinge (HG) loss, and Adam optimizer at specified learning rates (LRs).

| Architecture | $(D,G)$ LRs | Loss | Training | IS [23] | FID [6] | Speed$^3$ | Speedup | Samples |
|--------------|-------------|------|----------|---------|--------|----------|--------|---------|
| CNN          | $(2.0,2.0) \times 10^{-4}$ | NS   | C        | 7.21 ± 0.06 | 27.23 ± 0.96 | 26.9     |        | Fig. 4.1 |
|              |             |      | F        | 7.17 ± 0.05 | 27.91 ± 0.60 | 41.7     | 1.55×  |         |
|              |             |      | C        | 7.32 ± 0.12 | 25.42 ± 1.53 | 27.0     |        |         |
|              |             |      | I        | 7.32 ± 0.07 | 24.59 ± 1.13 | 40.4     | 1.50×  |         |
| ResNet       | $(4.0,1.0) \times 10^{-4}$ | NS   | C        | 7.66 ± 0.20 | 22.65 ± 1.50 | 14.9     |        |         |
|              |             |      | F        | 3.08 ± 0.37 | 118.2 ± 14.7 | 21.9     | 1.47×  |         |
|              |             |      | C        | 7.68 ± 0.15 | 19.93 ± 1.66 | 14.6     |        |         |
|              |             |      | I        | 4.11 ± 0.39 | 94.00 ± 6.32 | 21.1     | 1.45×  |         |
| ResNet       | $(4.0,0.5) \times 10^{-4}$ | NS   | C        | 7.59 ± 0.14 | 27.56 ± 1.17 |         |        | Fig. 4.3 |
|              |             |      | F        | 7.55 ± 0.22 | 26.97 ± 1.67 |         |        |         |
|              |             |      | C        | 7.76 ± 0.15 | 23.41 ± 1.15 |         |        |         |
|              |             |      | I        | 7.66 ± 0.11 | 23.49 ± 0.79 |         |        | Fig. 4.4 |

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