Conditional Activation GAN: improved Auxiliary Classifier GAN

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Note: This paper is separated from my other paper CASL-GAN (http://vixra.org/abs/1909.0061?ref=10946100).

Abstract

Conditional GAN is a GAN that can generate data with the desired condition from the latent vector. Among the variation of conditional GANs, currently, auxiliary classifier GAN is commonly used. In this study, propose a conditional activation GAN to reduce hyperparameter and improve training speed over auxiliary classifier GAN. Conditional activation loss is the sum of the losses of each GAN when creating a GAN for each condition, and since each GAN shares hidden layers, it does not increase the amount of computation much. Also, purpose mixed batch training to apply batch normalization in discriminator.

1. Introduction

Conditional GAN [1] is a GAN that can generate data with the desired condition from the latent vector. There are several studies on conditional GANs [2][3]. The most commonly used conditional GAN is Auxiliary Classifier GAN (AC-GAN) [4]. Loss of AC-GAN is used in AttGAN [5] and StarGAN [6] to generate an image with desired conditions. In this study, propose conditional activation GAN to reduce hyperparameter of AC-GAN, and improve training speed. Loss of conditional activation GAN is the sum of losses of each GAN that each GAN trains only one attribute. Because every GAN shares all hidden layers, it is possible to consider all GANs as one single GAN. Unlike AC-GAN using two losses (adversarial loss, classification loss), conditional activation GAN uses only one loss (conditional activation loss), which means it does not need to find the ratio of adversarial loss and classification loss. Also, conditional activation loss always produces meaningful gradients, whereas generator classification loss using cross-entropy produces meaningless gradients at the beginning of training.

In AC-GAN (or conditional activation GAN), applying batch normalization to discriminator distorts condition distribution of input batch. If discriminator applied batch normalization, the distribution of generated data batch tries to follow the distribution of real data batch. Likewise, condition distribution of generated data batch tries to follow the condition distribution of real data batch. This means that some data in the generated data batch may
ignore the input condition to follow the condition distribution of the real data batch. I suggest mixed batch training, which is composing batch always with the same ratio of real data and generated data, to keep condition distribution of batch same to apply batch normalization in the discriminator.

2. Conditional Activation GAN

2.1 Conditional Activation GAN

The loss of AC-GAN is as follows.

\[
L_D = L_{adv}^D + \lambda_{cls} L_{cls}^D
\]

\[
L_G = L_{adv}^G + \lambda_{cls} L_{cls}^G
\]

\[
L_{cls}^D = E_{x, att \sim P_r(x, att)}[-\log(D_{cls}(att|x))]
\]

\[
L_{cls}^G = E_{x', att' \sim P_g(x', att')[-\log(D_{cls}(att'|x'))]
\]

In \(x, att \sim P_r(x, att)\), \(x\) is real data, and \(att\) is the binary vector that expresses the attributes of real data. In \(x', att' \sim P_g(x', att')\), \(x'\) means generated data, and \(att'\) is the target binary vector to make \(x'\).

In the AC-GAN, adversarial loss trains model well because there are well known adversarial losses such as LSGAN [7] or WGAN-GP [8] that can produce meaningful gradients even if real data distribution and generated data distribution are far from each other. However, classification loss of AC-GAN, which is using cross-entropy, is hard to produce meaningful gradients if real data distribution and generated data distribution are far from each other because cross-entropy measures only KL-divergence.

Fig 1. Data distribution at the beginning of training using AC-GAN

In the early stage of learning, the generator classification loss \(L_{cls}^G\) does not produce meaningful gradients because the distance between Real A and Generated A, Real B and Generated B are too far from each other. Only adversarial loss produces meaningful gradients.

Fig 2. After some training using AC-GAN

As learning progresses to some degree with adversarial loss, when the real data distribution and the generated data distribution become somewhat similar, the generator classification
loss $L^c_{cls}$ begins to produce a meaningful gradient because real A and generated A, real B and generated B become somewhat similar.

Also, AC-GAN has important hyperparameters: adversarial loss weight and classification loss weight. If adversarial loss weight is too bigger than the classification loss weight, the generated data would not have the target condition. If classification loss weight is too bigger than adversarial loss weight, the data does not look real.

To solve these problems of AC-GAN, I propose conditional activation loss, which is similar to having multiple GANs that each GAN trains each attribute.

The following formula is an example of LSGAN adversarial loss.

$$L_{Dc} = E_{x,c \sim P_r(x,c)}[(D_c(x) - 1)^2] + E_{x' \sim P_{Gc}(x',1)}[D_c(x')^2]$$

$$L_{Gc} = E_{x' \sim P_{Gc}(x',1)}[D_c(x') - 1]^2$$

$c$ means one specific attribute among several attributes. GAN $c$ is the GAN that train about only attribute $c$.

$G_c$ and $D_c$ are generator and discriminator of GAN $c$. $G_c$ receives a binary activation value with a latent vector. If $G_c$ receives 1 as an activation value, $G_c$ tries to trick $D_c$, and $D_c$ tries to discriminate generated data as fake. If $G_c$ receives 0 as activation value, $G_c$ and $D_c$ don’t care about it (do not train). $D_c$ only tires of discriminating real data, which has attribute $c$ as real, and don’t care about other real data.

In $x, c \sim P_r(x,c)$, $x$ is real data which has attribute $c$. In $x' \sim P_{G_c}(x',1)$, $x'$ is generated data by $G_c$ when it receives latent vector and 1 as activation value.

$f^D_r$ is an adversarial loss of discriminator about real data. $f^D_g$ is an adversarial loss of discriminator about generated data. $f^G$ is an adversarial loss of generator.

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$$L_{Dc} = E_{x,c \sim P_r(x,c)}[(D_c(x) - 1)^2] + E_{x' \sim P_{Gc}(x',1)}[D_c(x')^2]$$

$$L_{Gc} = E_{x' \sim P_{Gc}(x',1)}[(D_c(x') - 1)^2]$$

Since each GAN shares all hidden layers, conditional activation loss can be changed as the following formula.
\[ L_{ca}^D = E_{x,att \sim P_r(x, att)}[f_r^D(D, x) \cdot att] + E_{x', att' \sim P_g(x', att')}[f_g^D(D, x') \cdot att'] \]

\[ L_{ca}^G = E_{x', att' \sim P_g(x', att')}[f_g^G(D, x') \cdot att'] \]

In \( x, att \sim P_r(x, att) \), \( x \) is real data, and \( att \) is the binary vector that expresses the attributes of real data. In \( x', att' \sim P_g(x', att') \), \( x' \) means generated data, and \( att' \) is the target binary vector to make \( x' \). \( \cdot \) is an inner product.

The following formula is an example of conditional activation loss with LSGAN adversarial loss.

\[ L_{ca}^D = E_{x,att \sim P_r(x, att)}[(D(x) - 1)^2 \cdot att] + E_{x', att' \sim P_g(x', att')}[(D(x'))^2 \cdot att'] \]

\[ L_{ca}^G = E_{x', att' \sim P_g(x', att')}[(D(x') - 1)^2 \cdot att'] \]

Also, in AC-GAN, when the output of classifier A is 0, that means input data does not have attribute A. However, in conditional activation GAN, GAN A does not care about attribute not-A. Therefore, to train attribute not-A, new GAN which trains attribute not-A should be added.

Using conditional activation loss with adversarial loss of LSGAN or WGAN-GP or other GAN can generate meaningful gradients at the beginning of the training when real data distribution and generated data distribution are far from each other. Also, conditional activation loss can replace adversarial loss and classification loss, which can reduce one important hyperparameter of AC-GAN. Conditional activation GAN loss has only one
hyperparameter: conditional activation loss weight, while AC-GAN loss has two hyperparameters: adversarial loss weight, classification loss weight.

2.2 Mixed batch training

In AC-GAN (or conditional activation GAN), applying batch normalization to discriminator distorts condition distribution of input batch. If discriminator applied batch normalization, the distribution of generated data batch tries to follow the distribution of real data batch. Likewise, condition distribution of generated data batch tries to follow the condition distribution of real data batch. This means that some data in the batch may ignore the input condition to follow the condition distribution of the real data batch. I suggest mixed batch training, which is composing batch always with the same ratio of real data and generated data, to keep condition distribution of batch same to apply batch normalization to the discriminator.

3. Material and methods

Used train dataset of MNIST handwriting number dataset [9]. Data size is 60000, resolution is 28x28 and channel size is 1.

Used tensorflow2.0. Model architecture used basic design of DCGAN [10]. However, used batch normalization on only discriminator, not generator.

Used conditional activation loss with LSGAN adversarial loss.

Used average of FID [11] for evaluation. Used all test dataset for calculate FID. Generated data size is same as each test dataset size. Since the MNIST dataset has one channel and their resolution is too low to input the inception network, triple the resolution and channel (84x84x3).

4. Results and Conclusions

Each row has same condition. Each col has same latent vector.
5. Discussion and Future works

Experiments show that conditional activation GAN can replace AC-GAN. Since there is one less hyperparameter than AC-GAN loss, conditional activation loss can significantly reduce the time to search for optimal hyperparameters. Further experimentation is needed to compare the training speed of conditional activation GAN and AC-GAN.

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7. Appendix

Results of CASL-GAN (Image-to-image translation GAN, http://vixra.org/abs/1909.0061?ref=10946100), which is using conditional activation GAN loss. All first pictures are original pictures, second pictures are generated pictures, third pictures are mask images, and fourth pictures are generated segment images.
8. References

Conditional Generative Adversarial Nets
https://arxiv.org/abs/1411.1784

Generative Attribute Controller with Conditional Filtered Generative Adversarial Networks

[3] Xi Chen, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, Pieter Abbeel
InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
https://arxiv.org/abs/1606.03657

[4] Augustus Odena, Christopher Olah, Jonathon Shlens
Conditional Image Synthesis With Auxiliary Classifier GANs
https://arxiv.org/abs/1610.09585

[5] Zhenliang He, Wangmeng Zuo, Meina Kan, Shiguang Shan, Xilin Chen
AttGAN: Facial Attribute Editing by Only Changing What You Want
https://arxiv.org/abs/1711.10678

[6] Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Kim, Jaegul Choo
StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation
https://arxiv.org/abs/1711.09020

[7] Xudong Mao, Qing Li, Haoran Xie, Raymond Y.K. Lau, Zhen Wang, Stephen Paul Smolley
Least Squares Generative Adversarial Networks
https://arxiv.org/abs/1611.04076

[8] Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, Aaron Courville
Improved Training of Wasserstein GANs
https://arxiv.org/abs/1704.00028

[9] Yann LeCun, Corinna Cortes, Christopher J.C. Burges
THE MNIST DATABASE of handwritten digits
Unsupervised Representation Learning with
Deep Convolutional Generative Adversarial
Networks

https://arxiv.org/abs/1511.06434

Unterthiner, Bernhard Nessler, Sepp Hochreiter
GANs Trained by a Two Time-Scale Update Rule
Converge to a Local Nash Equilibrium

https://arxiv.org/abs/1706.08500