Complementary Generative adversarial Nets

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Abstract

1. Introduction

Generative adversarial networks (GANs) are proposed to model the distribution of real data without estimating explicit density function. This adversarial learning method has achieved generating high-fidelity data for various tasks[1, 3, 8].

With the success of GANs, the conditional versions of GANs are proposed, which are extended to generate data with conditional label. Among them, Conditional GANs (CGANs), Auxiliary Classifier GANs (ACGAN) and Projection Spectral-Norm GANs (PSN-GAN) are widely used. By modeling the conditional distribution of data given label, GANs are allowed to selectively generate data with label. During the training, class label also helps improve fidelity and stability of GANs which may suffer collapse and gradient diminish on dataset of high variance.

However, there are limited availability of accurate class-labeled data due to the laboring cost and time cost, which discourages the performance of Conditional GANs highly. In real world, negative labeled data are more reliable and easily to generate. In contrast to the standard classification paradigm where the true (or possibly noisy) class is given to each training pattern, complementary-label learning only uses training patterns each equipped with a complementary label. This only specifies one of the classes that the pattern does not belong to. Also, These negative complementary labeled data gives a potential for compensating the rareness of ordinary accurate labeled data. Along with complementary learning, the converged speed is slow and also a plenty of training data are needed. Thus, we propose to incorporate complementary learning with semi-supervised learning, which can generate more robust labeled data though conditional GANs and in turn help training classification model.

2. Related Works

Deep generative models Generative model are proposed model the distribution of data which is a basic topic in computer vision and machine learning. Due to its property of learning continuous distribution, it gives a hint for understanding the latent relationship between data. In recent years, there have been many deep generative models emerging, such as Variational AutoEncoders (VAEs) [6] and Generative Adversarial Nets (GANs) [2]. This two methods all avoid modeling the density function over real data, VAEs models the distribution over latent variables and GANs approaching the data distribution by a two-plays game. GANs makes a more important role in most recently as it can generate data with more details, but the instability is also a vital problem.

Conditional GANs As mentioned in section 1, Conditional GANs are able to model the disentanglement by given labels. The pioneer work Conditional GANs (CGANs) [7] naively fed label y into the generative network and discriminator network as pioneer work. In later, Auxiliary Classifier GANs (ACGAN) [9] introduce a classifier in the bottom layer of discriminator networks, which improve the performance and stability of Conditional GANs. Nonetheless, it is still challenging for generating diversity and fidelity in some dataset with more classes like Imagenet. To solve this on Conditional GANs, some variance of Wasserstein GAN (WGANs) [1] are proposed to stable the training which introduce Lipschitz Constraint on discriminator networks. In our work, we will make full use of these method.

Complementary Learning There are three works done for complementary learning, the first [4] provide a unbiased estimator for training networks by complementary labels. And these complementary labels are all uniformly sampled from different class. However, in real world, these complementary label may exit bias and are not uniformly given for each class. Thus the second work [10] propose a transformation matrix which can straightly transform complementary learning to simple ordinary learning method.

The last one [5] derives an unbiased risk estimator for arbitrary losses and models. In this paper, our model are based on the second method which can be simply plugged into ACGANs.

3. Method

$$L_S = E[\log D((X_{real})] + E[\log(1 - D(G(z))] \quad (1)$$

$$L_{CD} = E_{c\sim y}[\log D_c(C = c|X_{real})] + E_{c\sim \overline{y}}[\log D_c(C = c|X_{real})] \quad (2)$$

$$L_{CG} = E_{c\sim y}[\log D_c(C = c|G(z|c))] \quad (3)$$

D is trained to maximize $L_S + L_{CD}$ while G is trained to maximize $L_{CG} - L_S$.

$$L_{semi-Classification} = E_{c\sim y}[\log D_c(C = c|X_{real})] + E_{c\sim y}[\log D_c(C = c|\hat{G}(z|c))] \quad (4)$$

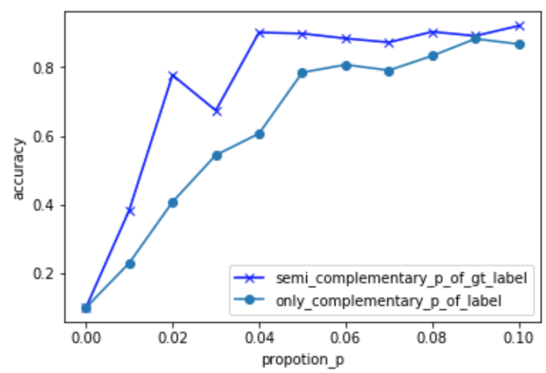
In semi-supervised training, we train classification model with ground truth data and generative data generated by pretrained $\hat{G}$.

4. Experiments

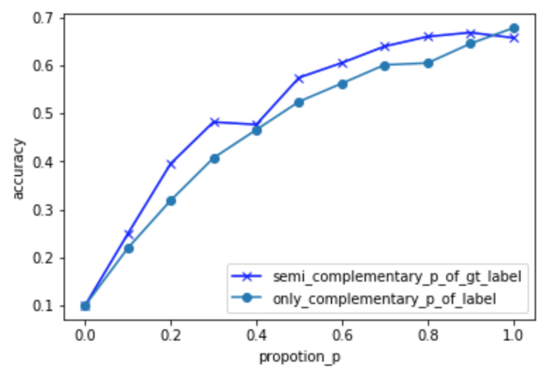
5. Ablation Study

6. Analysis

7. Conclusion



(a) MNIST



(b) CIFAR10

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