Regularizing Discriminative Capability of CGANs for Semi-Supervised Generative Learning

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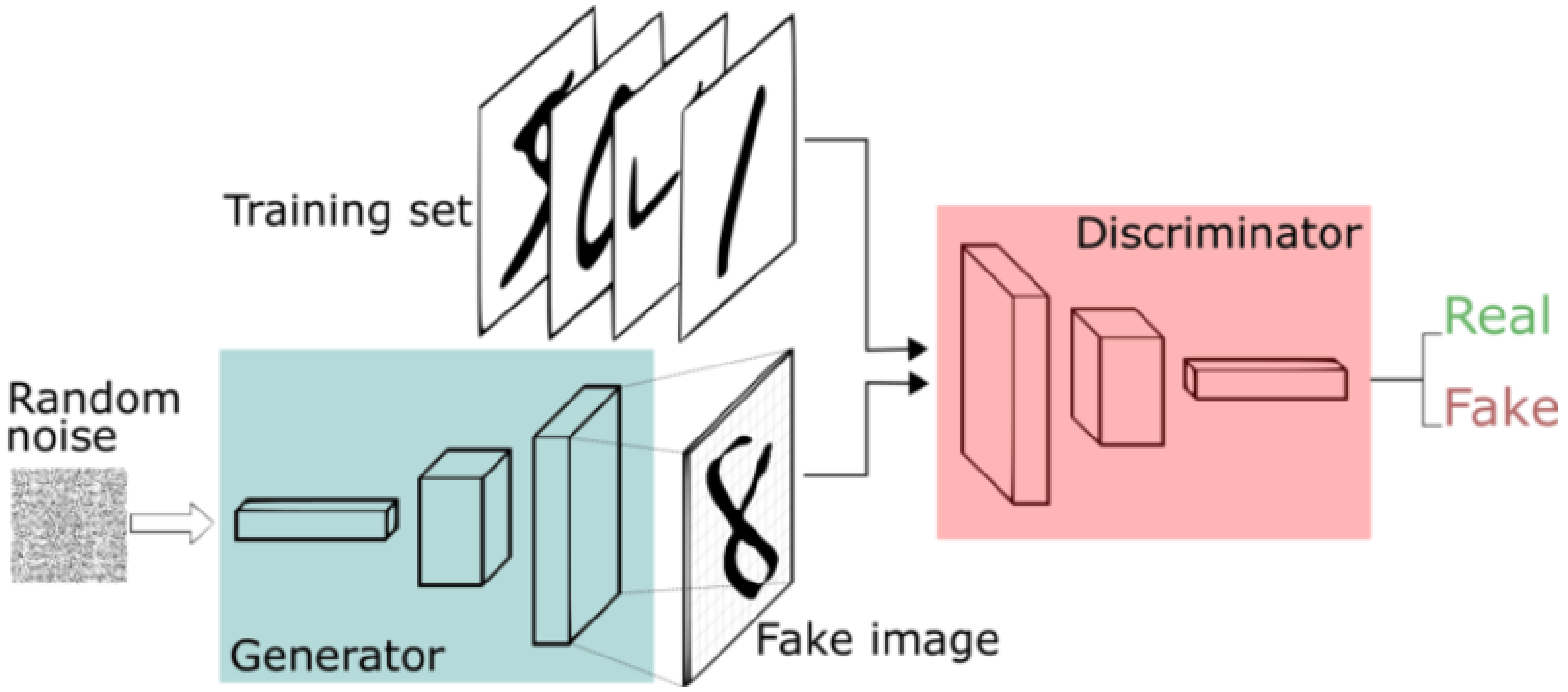
GAN

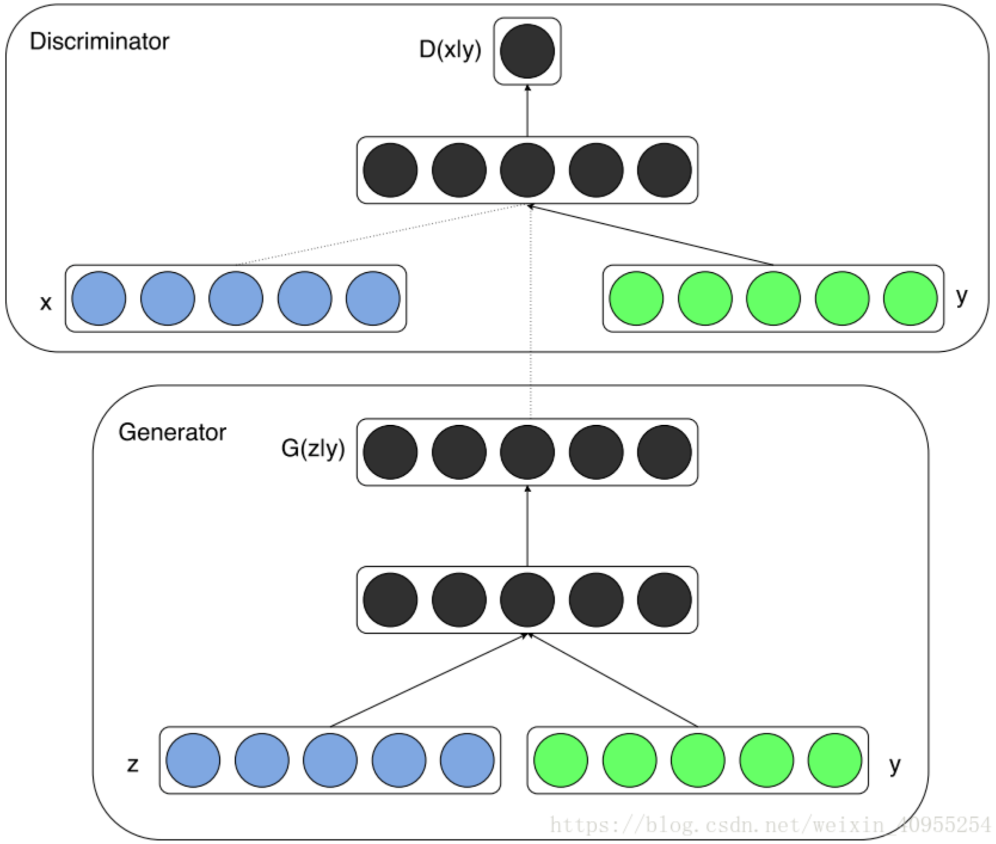
Input:Training set without label



Goal: generating some date with training set's distribution

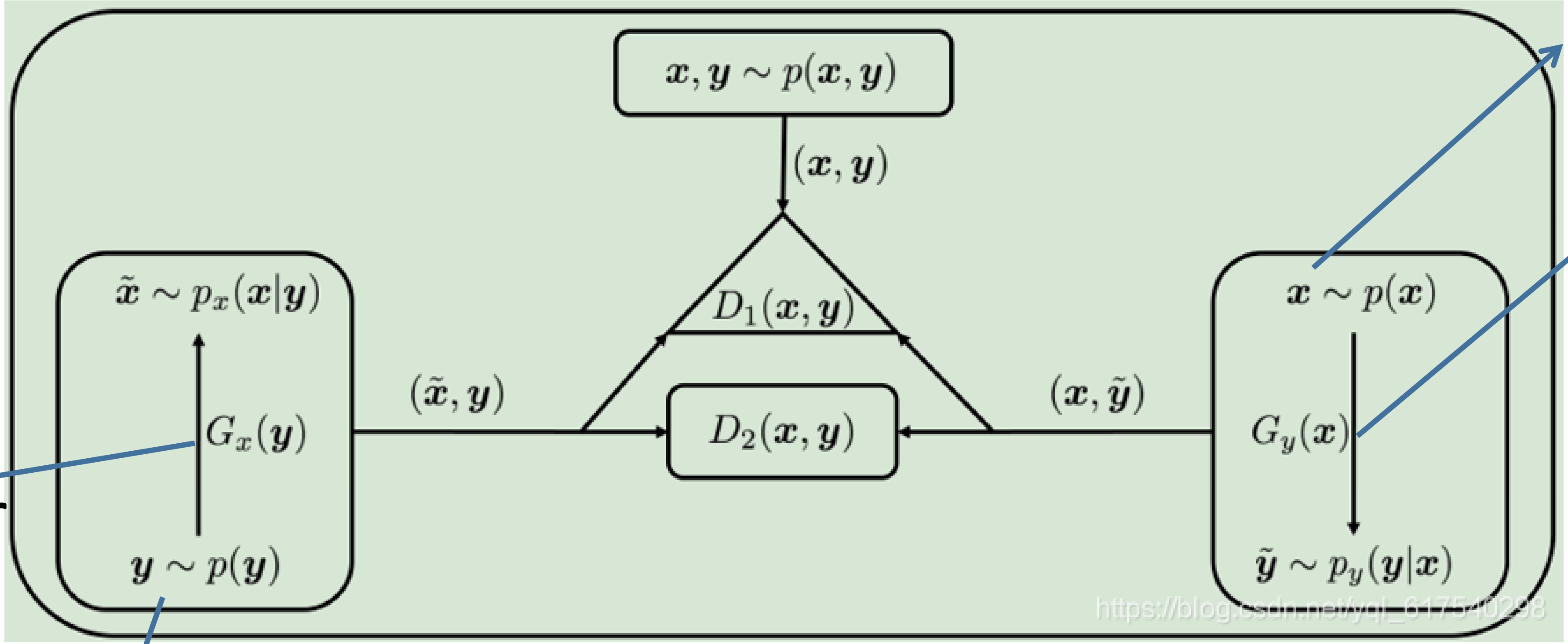
Supervised GAN

Input: traning set with label



Generating some date with training set's distribution and specifical label——y

Semi-Supervised GAN



unlabeled data

classifier

generator

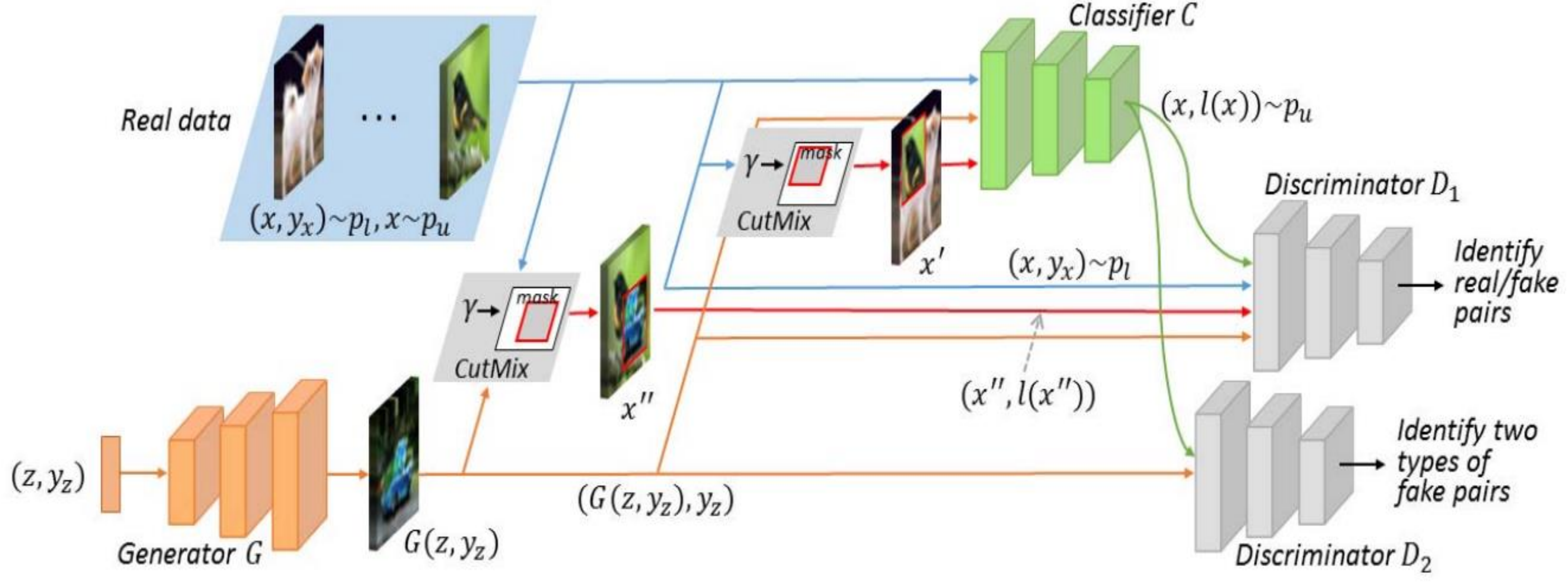
input： noisy and label y

Motivation

imbalance between real labeled data and fake data in the adversarial learning process

The discriminator tends to memorize the real labeled instances and reject unseen types of instances even from the distribution of true data

Proposed Methods



Cut-Mix

$$x' = \texttt{CutMix}(x_a, x_b, \gamma) \qquad \gamma \sim \texttt{Beta}(\alpha, \alpha)$$

$$= M(\gamma) \odot x_a + \big(I - M(\gamma)\big) \odot x_b,$$

$$M(\gamma) \in \{0, 1\}^{W \times H}$$

$$M(\gamma)(u, v) = \begin{cases} 0, & \text{if } (u, v) \in B(\gamma), \\ 1, & \text{otherwise}, \end{cases}$$

$$B(\gamma) \quad : \quad (u_0 + W\sqrt{1-\gamma}, v_0 + H\sqrt{1-\gamma}).$$

Goal:

$$t(x') = \gamma t(x_a) + (1-\gamma) t(x_b).$$

The goal of C

$$\min_{C} L_{adv}^{C} + \mathrm{E}_{z\sim p_z}\left[\mathtt{CE}(y_z, C(G(z, y_z)))\right] + \mathrm{E}_{x'\sim p'_l}\left[\mathtt{CE}(t(x'), C(x'))\right] + \mathrm{E}_{x'\sim p'_u}\left[\mathtt{MSE}(t(x'), f_C(x')\right],$$

$$L_{adv}^{C} = \mathrm{E}_{x\sim p_u}\left[\mathtt{max}(C(x)) \log\left(1 - D_1(x, l(x))\right) + \mathtt{max}(C(x)) \log(1 - D_2(x, l(x)))\right],$$

Expriments

Table 1. Synthesis qualities of our R^3-CGAN and competing generative models on SVHN, CIFAR-10, CIFAR-100 and FaceScrub-100.

	SVHN (1k)		CIFAR-10 (4k)		CIFAR-100 (10k)		FaceScrub-100 (2k)	
Method	IS	FID	IS	FID	IS	FID	IS	FID
ImprovedGAN [32]	-	-	5.56±0.28	47.25	-	-	-	-
Triple-GAN [16]	-	-	5.77±0.14	47.08	-	-	-	-
Triangle-GAN [8]	2.75±0.02	36.56	6.56±0.07	35.31	-	-	-	-
EnhancedTGAN [40]	2.87±0.05	22.99	7.23±0.09	25.64	4.86±0.04	65.11	1.57±0.02	57.58
Baseline	2.66±0.02	45.03	6.57±0.06	37.21	4.29±0.06	72.39	1.66±0.03	31.21
R^3-CGAN	**2.99±0.02**	**10.87**	**7.42±0.05**	**20.34**	**7.49±0.01**	**26.29**	**1.73±0.02**	**25.28**

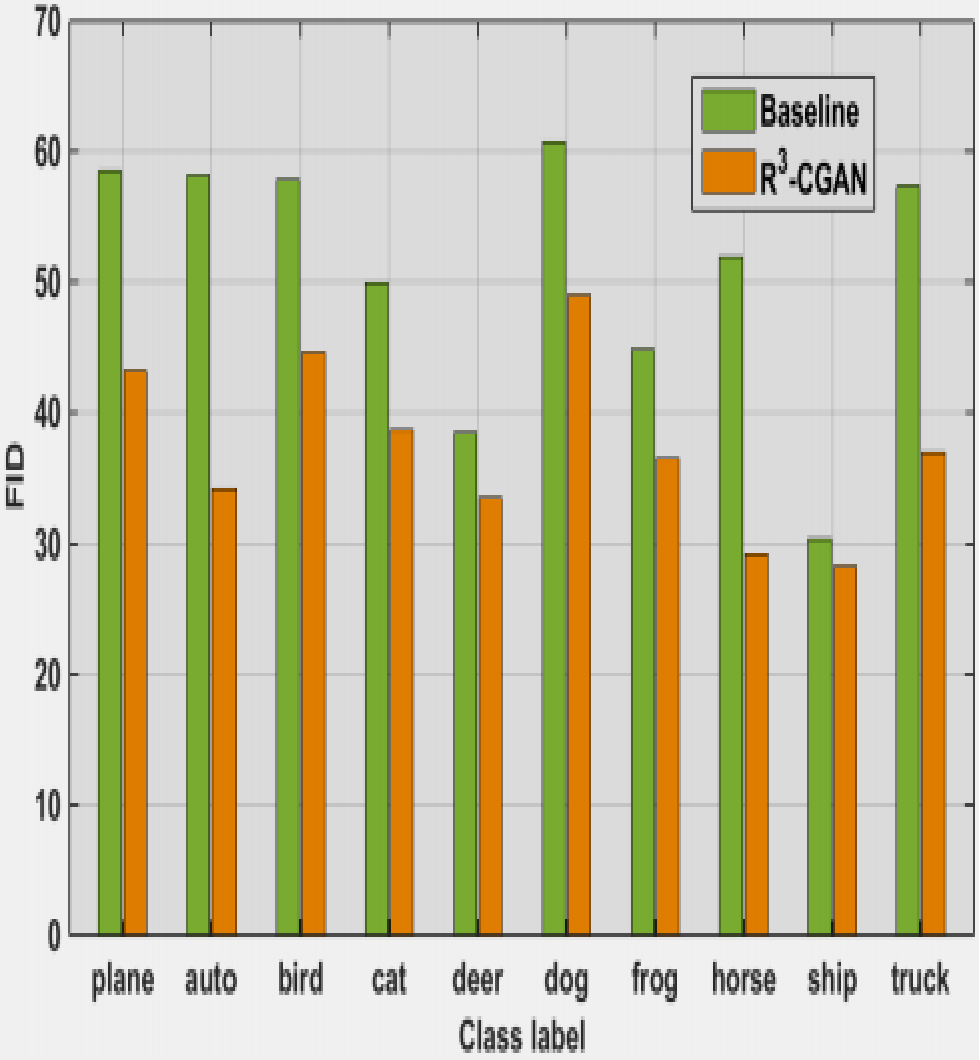


Table 2. Ablation experiment results of the proposed R^3-CGAN and variants on CIFAR-10 and CIFAR-100.

	CIFAR-10 (4k)		CIFAR-100 (10k)	
Method	IS	FID	IS	FID
Baseline	6.57±0.06	37.21	4.29±0.06	72.39
+ R^3-Reg. on D_1	**7.03±0.07**	**25.30**	**7.02±0.10**	**31.18**
Improvement	↑ 0.46	↓ 11.91	↑ 2.73	↓ 41.21
Baseline (ful. sup.)	7.07±0.08	26.49	7.11±0.06	32.39
+ R^3-Reg. on D_1	**7.78±0.07**	**17.98**	**7.83±0.14**	**23.45**
Improvement	↑ 0.71	↓ 8.51	↑ 0.72	↓ 8.94
R^3-CGAN	**7.42±0.05**	**20.34**	**7.49±0.01**	**26.29**
w/o R^3-Reg. on D_1	6.82±0.09	32.68	5.33±0.05	55.26
w/o R^3-Reg. on C	7.14±0.07	22.52	7.26±0.06	29.11

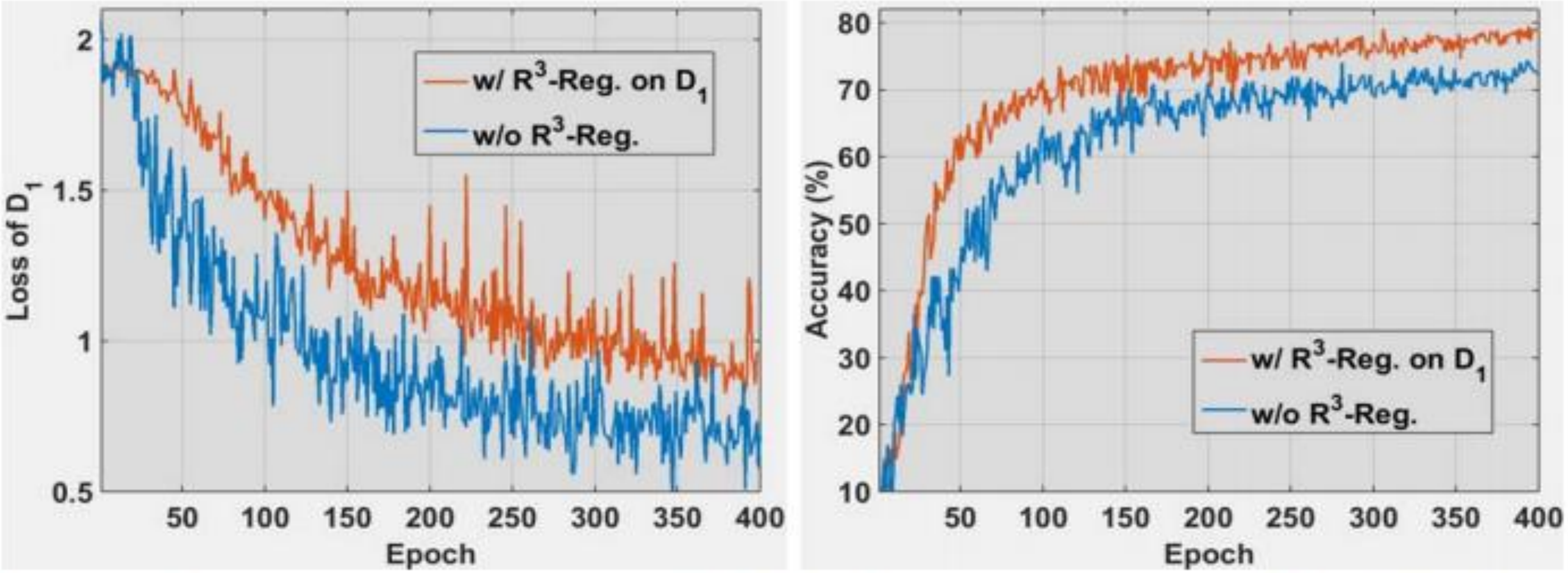


Figure 5. An experiment on CIFAR-10 (4k) to verify the effectiveness of the R^3-regularization on the discriminator D_1. The left subfigure shows that it is harder for D_1 to identify the complex instances constructed via CutMix. The right subfigure shows that more synthesized images are correctly classified by the classifier when applying this regularization, which indicates that the quality and discriminability of synthesized images are improved.

Classification Task

Table 3. Test error rates (%) of the proposed R^3-CGAN and previous state-of-the-art methods on SVHN and CIFAR-10.

Method	SVHN (1k)	CIFAR-10 (4k)
Ladder Network [29]	-	20.40±0.47
SPCTN [41]	7.37±0.30	14.17±0.27
Π-model [15]	4.82±0.17	12.36±0.31
Temporal Ensemb. [15]	4.42±0.16	12.16±0.24
Mean Teacher [36]	3.95±0.19	12.31±0.28
VAT [23]	3.74±0.09	11.96±0.10
VAdD [26]	4.16±0.08	11.68±0.19
SNTG+Π-model [18]	3.82±0.25	11.00±0.13
Deep Co-Train [27]	3.61±0.15	9.03±0.18
CCN [42]	3.36±0.18	8.80±0.24
ICT [38]	3.89±0.04	7.29±0.02
CatGAN [35]	-	19.58±0.58
ImprovedGAN [32]	8.11±1.30	18.63±2.32
ALI [7]	7.42±0.65	17.99±1.62
Triple-GAN [16]	5.77±0.17	16.99±0.36
Triangle-GAN [8]	-	16.80±0.42
GoodBadGAN [5]	4.25±0.03	14.41±0.03
CT-GAN [39]	-	9.98±0.21
EnhancedTGAN [40]	2.97±0.09	9.42±0.22
Baseline	5.47±0.43	13.51±0.58
R^3-CGAN	**2.97±0.05**	**6.69±0.28**

Table 4. Test error rates (%) of the proposed R^3-CGAN and previous state-of-the-art methods on CIFAR-100 and FaceScrub-100.

Method	CIFAR-100 (10k)	FaceScrub-100 (2k)
Π-model [15]	39.19±0.36	23.72±0.19
Temporal Ensemb. [15]	38.65±0.51	22.38±0.16
SNTG+Π-model [18]	37.97±0.29	-
Deep Co-Train [27]	34.63±0.14	-
CCN [42]	35.28±0.23	-
EnhancedTGAN [40]	36.18±0.37	16.08±0.24
Baseline	35.95±0.30	24.03±0.55
R^3-CGAN	**32.66±0.21**	**6.96±0.43**