Conditional GANs with Auxiliary Discriminative Classifier

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Research Problem

Conditional generative adversarial networks (GANs) aim at learning the joint distribution $P_{X,Y}$ of data $x \in \mathcal{X}$ and labels $y \in \mathcal{Y}$ for conditional data generation.

$$Q_{X,Y} \approx P_{X,Y}, \tag{1}$$

with $Q_{X,Y} = G_\sharp(P_Z \times P_Y)$ denoting the generated joint data-label distribution.

Implement a class-conditional generator $G : \mathcal{Z} \times \mathcal{Y} \to \mathcal{X}$

- conditional batch normalization (de Vries et al., 2017).

Train the class-conditional generator

- conditional discriminator (Mirza & Osindero, 2014; Miyato & Koyama, 2018) or auxiliary classifier (Gong et al., 2019; Odena et al., 2017).

Related Method

The common AC-GAN (Odena et al., 2017) uses an auxiliary classifier to train the generator but suffers from the low intra-class diversity issue of the generated samples.

$$\max_{D,C} V(G,D) + \lambda \cdot (\mathbb{E}_{x,y\sim P_{X,Y}}[\log C(y|x)]), \tag{2}$$

$$\min_{G} V(G,D) - \lambda \cdot (\mathbb{E}_{x,y\sim Q_{X,Y}}[\log C(y|x)]), \tag{3}$$

where $V(G,D)$ denotes the adversarial game between the discriminator and generator.

The optimal classifier

$C^*(y|x) = \frac{p(x,y)}{p(x)}$. **[ISSUE]** C^* is NOT aware of $Q_{X,Y}$.

Learning objective for the generator under the optimal discriminator and classifier

$\min_G \mathrm{JS}(Q_X \| P_X) + \lambda \cdot (\mathrm{KL}(Q_{X,Y} \| P_{X,Y}) - \mathrm{KL}(Q_X \| P_X) + H_Q(Y|X))$.

Related Method

The original AC-GAN (Odena et al., 2017) still suffers from the same issue.

$$\max_{D,C} V(G,D) + \lambda \cdot (\mathbb{E}_{x,y\sim P_{X,Y}}[\log C(y|x)] + \mathbb{E}_{x,y\sim Q_{X,Y}}[\log C(y|x)]), \tag{4}$$

$$\min_{G} V(G,D) - \lambda \cdot (\mathbb{E}_{x,y\sim Q_{X,Y}}[\log C(y|x)]). \tag{5}$$

The optimal classifier

$C^*(y|x) = \frac{p(x,y)+q(x,y)}{p(x)+q(x)}$. **[ISSUE]** C^* is NOT distinguished between $P_{X,Y}$ and $Q_{X,Y}$.

Learning objective for the generator under the optimal discriminator and classifier

$\min_G \mathrm{JS}(Q_X \| P_X) + \lambda \cdot (\mathrm{KL}(Q_{X,Y} \| P_{X,Y}) - \mathrm{KL}(Q_X \| P_X) + H_Q(Y|X))$ when $Q = P$.

Proposed Method

We propose an auxiliary discriminative classifier $C_{\mathrm{d}} : \mathcal{X} \to \mathcal{Y}^{+} \cup \mathcal{Y}^{-}$ that classifies the real and generated data with different class-labels for GANs (called ADC-GAN).

$$\max_{D,C} V(G,D) + \lambda \cdot (\mathbb{E}_{x,y \sim P_{X,Y}}[\log C_{\mathrm{d}}(y^{+}|x)] + \mathbb{E}_{x,y \sim Q_{X,Y}}[\log C_{\mathrm{d}}(y^{-}|x)]), \qquad (6)$$

$$\min_{G} V(G,D) - \lambda \cdot (\mathbb{E}_{x,y \sim Q_{X,Y}}[\log C_{\mathrm{d}}(y^{+}|x)] - \mathbb{E}_{x,y \sim Q_{X,Y}}[\log C_{\mathrm{d}}(y^{-}|x)]). \qquad (7)$$

The optimal discriminative classifier

$C_{\mathrm{d}}^{*}(y^{+}|x) = \frac{p(x,y)}{p(x)+q(x)}$, $C_{\mathrm{d}}^{*}(y^{-}|x) = \frac{q(x,y)}{p(x)+q(x)}$. C_{d}^{*} is aware of and distinguishes between $P_{X,Y}$ and $Q_{X,Y}$ so that it can provide the difference between them to the generator.

Learning objective for the generator under the optimal discriminator and classifier

$\min_{G} \mathrm{JS}(Q_X \| P_X) + \lambda \cdot \mathrm{KL}(Q_{X,Y} \| P_{X,Y})$.

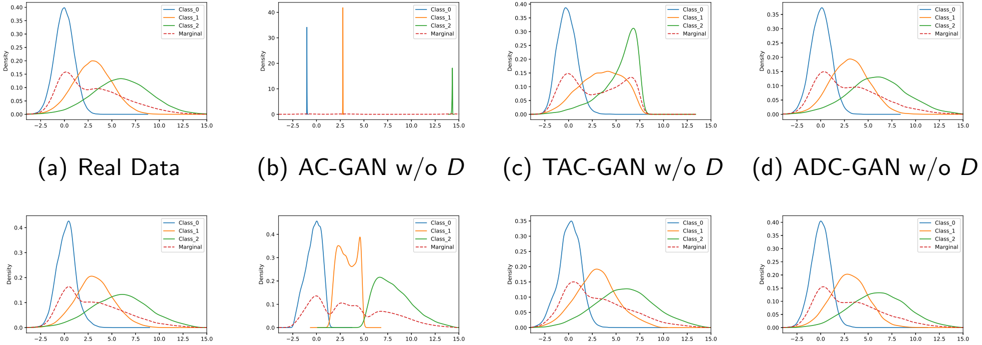
Competing Methods

- TAC-GAN (Gong et al., 2019): twin auxiliary classifiers $C : \mathcal{X} \to \mathcal{Y}$ trained on $P_{X,Y}$ and $C_{\mathrm{mi}} : \mathcal{X} \to \mathcal{Y}$ trained on $Q_{X,Y}$.
- PD-GAN (Miyato & Koyama, 2018): projection discrimnator $D_{\mathrm{p}} : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$.

Table: Learning objective for the generator under the optimal discriminator and classifier.

Method	Theoretical learning objective for the generator
AC-GAN	$\mathrm{JS}(P_X \| Q_X) + \lambda \cdot (\mathrm{KL}(Q_{X,Y} \| P_{X,Y}) - \mathrm{KL}(Q_X \| P_X) + H_Q(Y\|X))$
TAC-GAN	$\mathrm{JS}(P_X \| Q_X) + \lambda \cdot (\mathrm{KL}(Q_{X,Y} \| P_{X,Y}) - \mathrm{KL}(Q_X \| P_X))$
ADC-GAN	$\mathrm{JS}(P_X \| Q_X) + \lambda \cdot (\mathrm{KL}(Q_{X,Y} \| P_{X,Y}))$
PD-GAN	$\mathrm{JS}(Q_{X,Y} \| P_{X,Y})$

Experimental Results



(a) Real Data (b) AC-GAN w/o D (c) TAC-GAN w/o D (d) ADC-GAN w/o D

(e) PD-GAN (f) AC-GAN w/ D (g) TAC-GAN w/ D (h) ADC-GAN w/ D

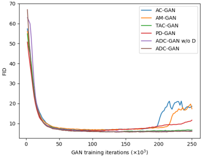
Figure: Qualitative comparison of distribution learning results on the synthetic data.

Experimental Results

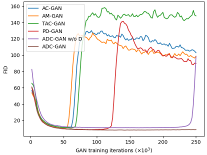
Table: FID (↓) and Intra-FID (↓) (generation quality) and Accuracy (↑) (representation quality) comparisons on CIFAR-10, CIFAR-100, and Tiny-ImageNet, respectively.

Datasets	Metrics	PD-GAN	AC-GAN	TAC-GAN	ADC-GAN
CIFAR-10	FID	6.23	6.50	5.83	**5.66**
	Intra-FID	48.90	57.67	56.67	**40.45**
	Accuracy	66.22	84.69	88.27	**89.51**
CIFAR-100	FID	8.70	11.24	10.38	**8.12**
	Intra-FID	51.15	83.06	79.59	**49.24**
	Accuracy	37.89	55.26	60.03	**64.24**
Tiny-ImageNet	FID	26.10	25.02	21.12	**19.02**
	Intra-FID	66.23	99.04	95.48	**63.05**
	Accuracy	27.79	44.59	44.44	**48.89**

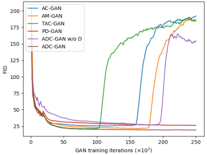
Experimental Results



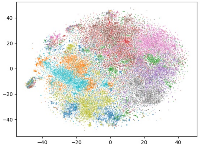
(a) CIFAR-10



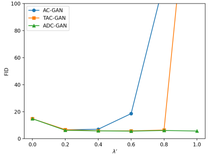
(b) CIFAR-100



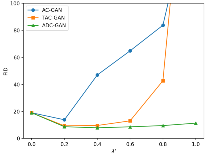
(c) Tiny-ImageNet



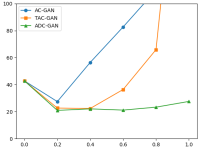
(d) PD-GAN



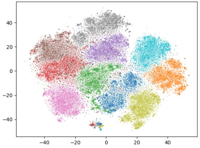
(e) CIFAR-10



(f) CIFAR-100



(g) Tiny-ImageNet



(h) ADC-GAN

Figure: (a,b,c) show the training FID curve. (e,f,g) show the FID of objective function $(1-\lambda)V(G,D)+\lambda V(G,C)$ with different λ. (d,h) show the TSNE of D/C on CIFAR-10.

Summary

We propose ADC-GAN, a novel conditional generative adversarial network with an auxiliary discriminative classifier, for faithful conditional generative modeling.

We theoretically analyze that the generator of ADC-GAN can faithfully learn the joint distribution even without the discriminator, making the proposed ADC-GAN

- robust to the value of the coefficient hyperparameter λ.
- robust to the selection of the GAN loss $V(G, D)$.
- stable during training.

Thank you for your attention!
Please check out our paper for more details.