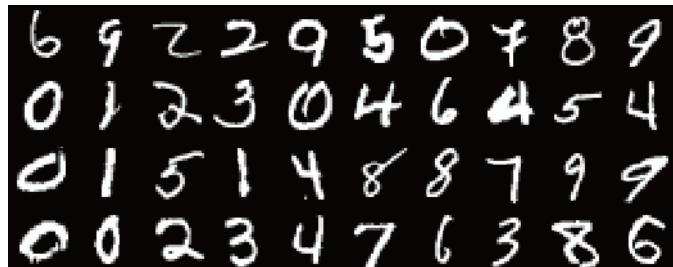


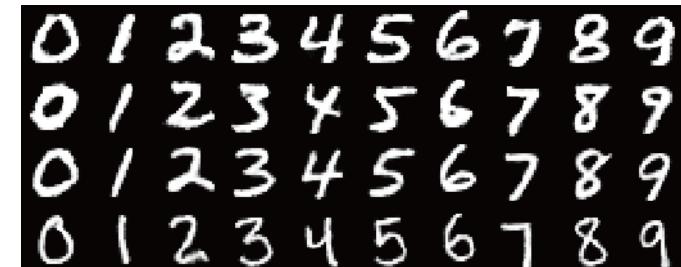
Label-Noise Robust Generative Adversarial Networks

Training data



Noisy labeled

rcGAN



*Conditioned on *clean* labels*

Takuhiro Kaneko¹ Yoshitaka Ushiku¹ Tatsuya Harada^{1, 2}

¹The University of Tokyo

²RIKEN



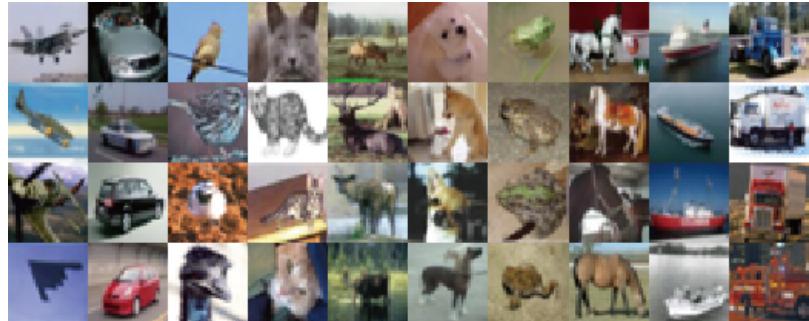
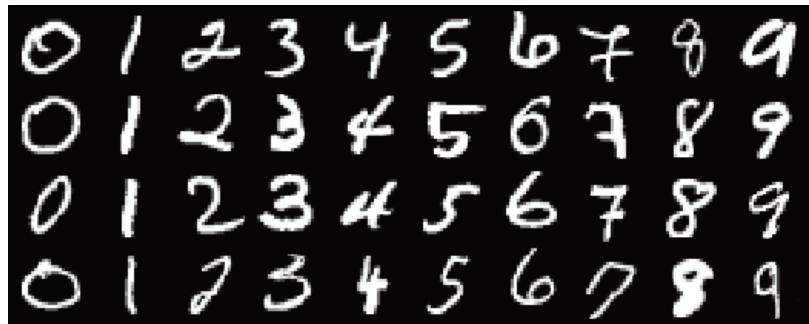
THE UNIVERSITY OF TOKYO



Objective: Label-noise robust conditional image generation

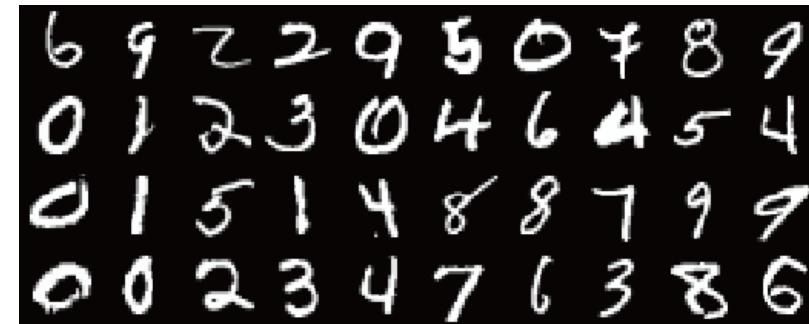
Our goal is to construct a **label-noise robust conditional image generator**
that can reproduce ***clean* labeled data (a)**
even when ***noisy* labeled data (b)** are only available during the training.

(a) *Clean* labeled data



Unavailable

(b) *Noisy* labeled data

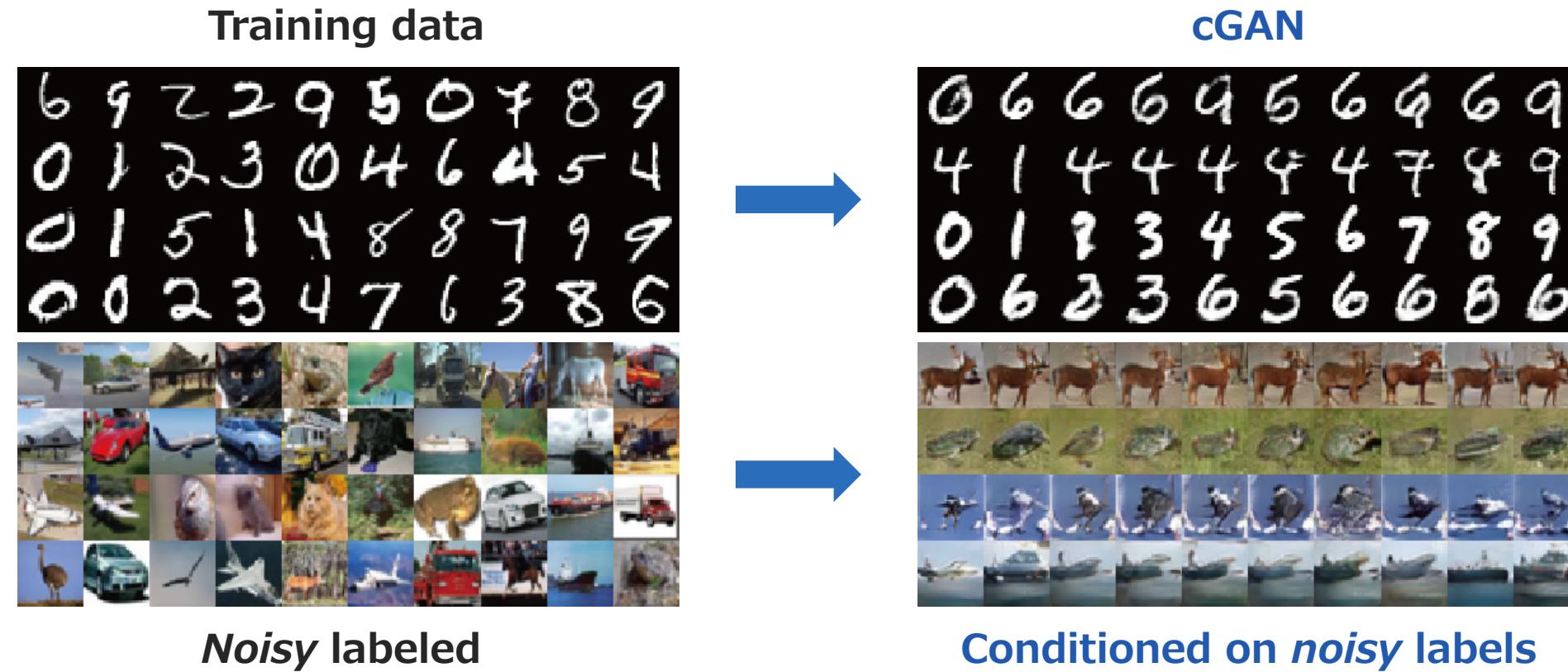


Available

Challenge: Limitation of naïve conditional generative models

Naïve **conditional generative models** (e.g., **AC-GAN** [1], **cGAN** [2, 3])

attempt to construct a generator conditioned on observable labels
(i.e., ***noisy labels*** in this case).

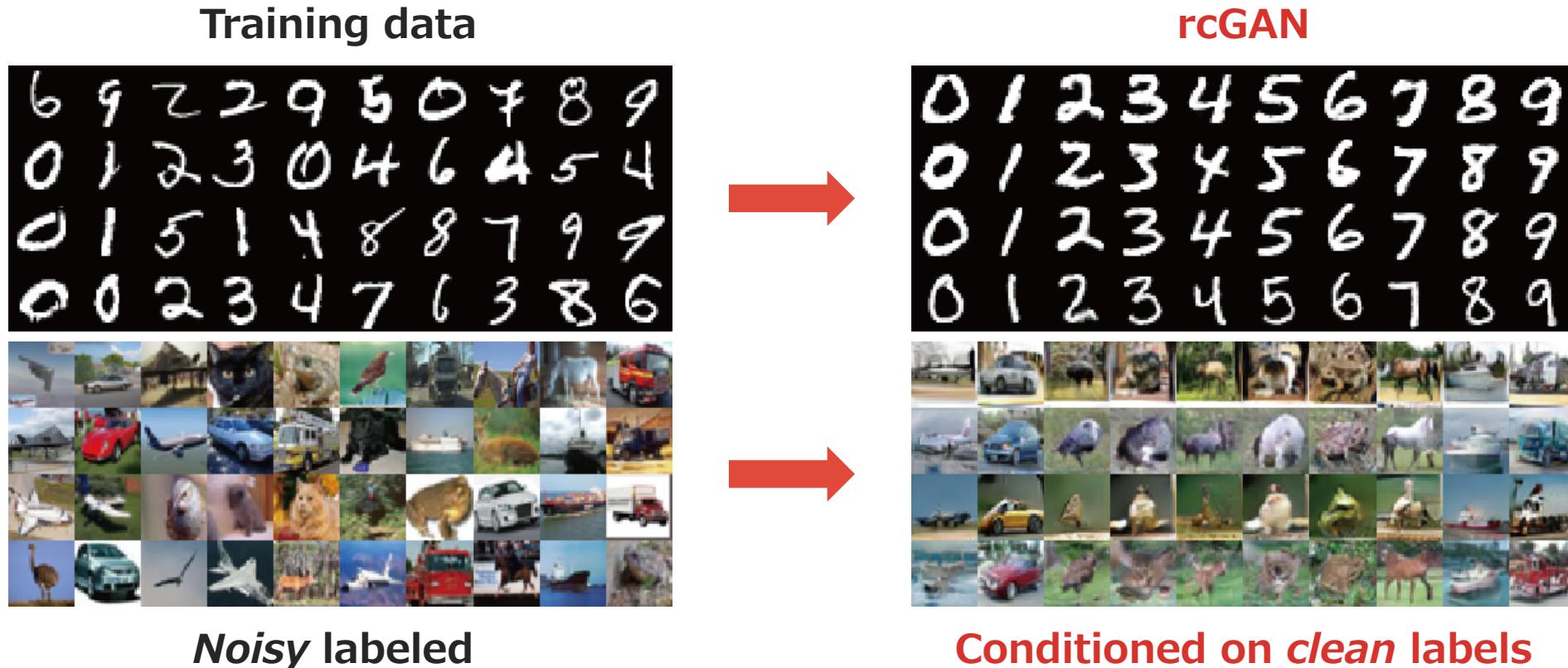


AC-GAN: auxiliary classifier GAN, cGAN: conditional GAN

[1] Odena et al. ICML 2017. [2] Mirza & Osindero. arXiv 2014. [3] Miyato & Koyama. ICLR 2018.

Contribution: Proposal of label-noise robust GANs

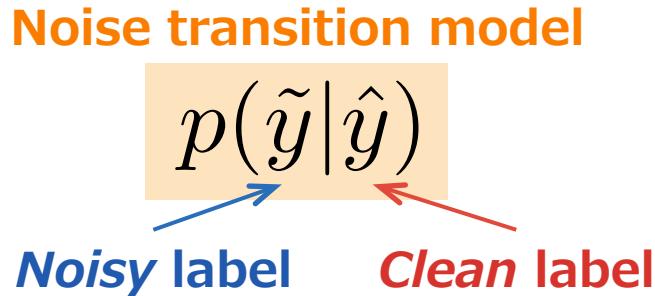
To overcome this limitation, we propose **label-noise robust GANs (rGANs)** that can constructs a generator conditioned on ***clean* labels** even when trained with ***noisy* labeled data**.



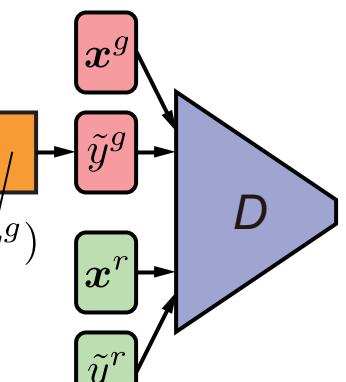
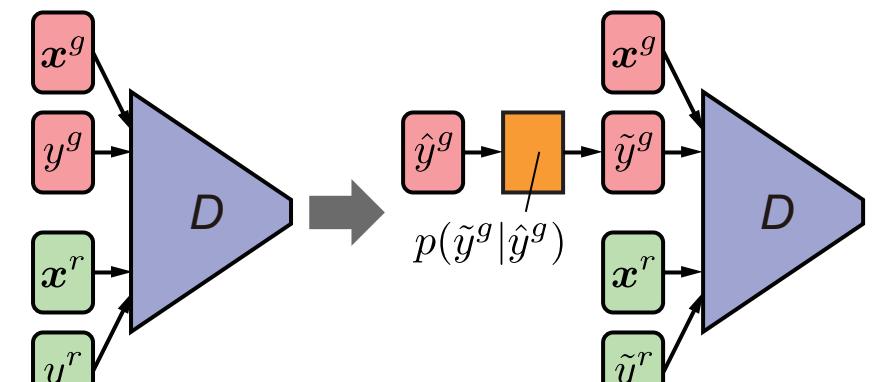
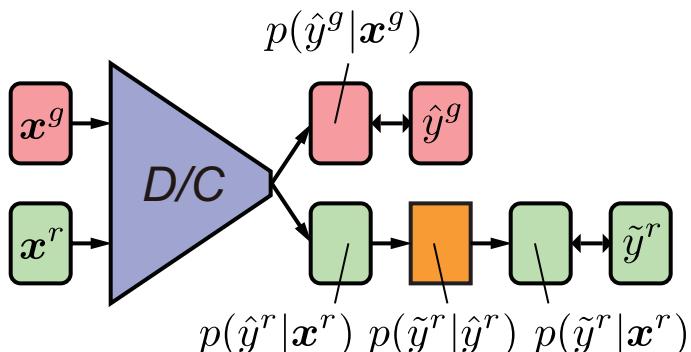
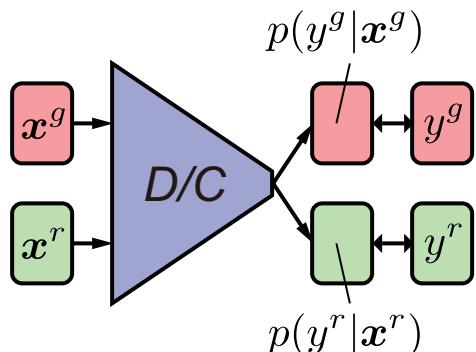
rGAN: label-noise robust conditional GAN

Main idea: Incorporation of noise transition model

We incorporate a **noise transition model** into naïve conditional GANs [1, 2, 3].



Two variants



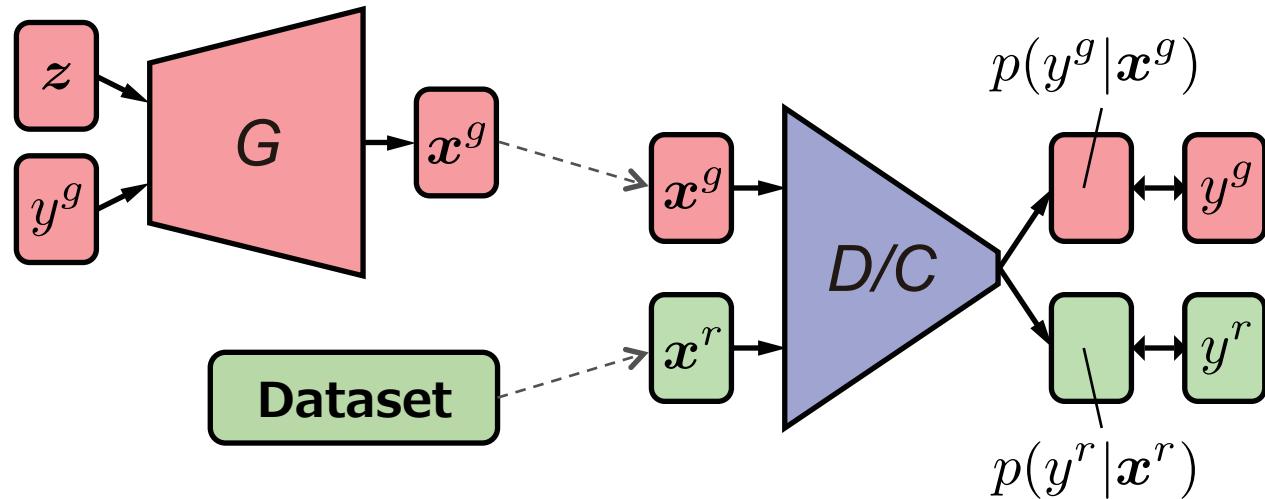
Baseline: AC-GAN

Auxiliary classifier GAN [1]

Generator:

$$G(z, y^g)$$

Discriminator/Classifier: $D(x) / C(y|x)$



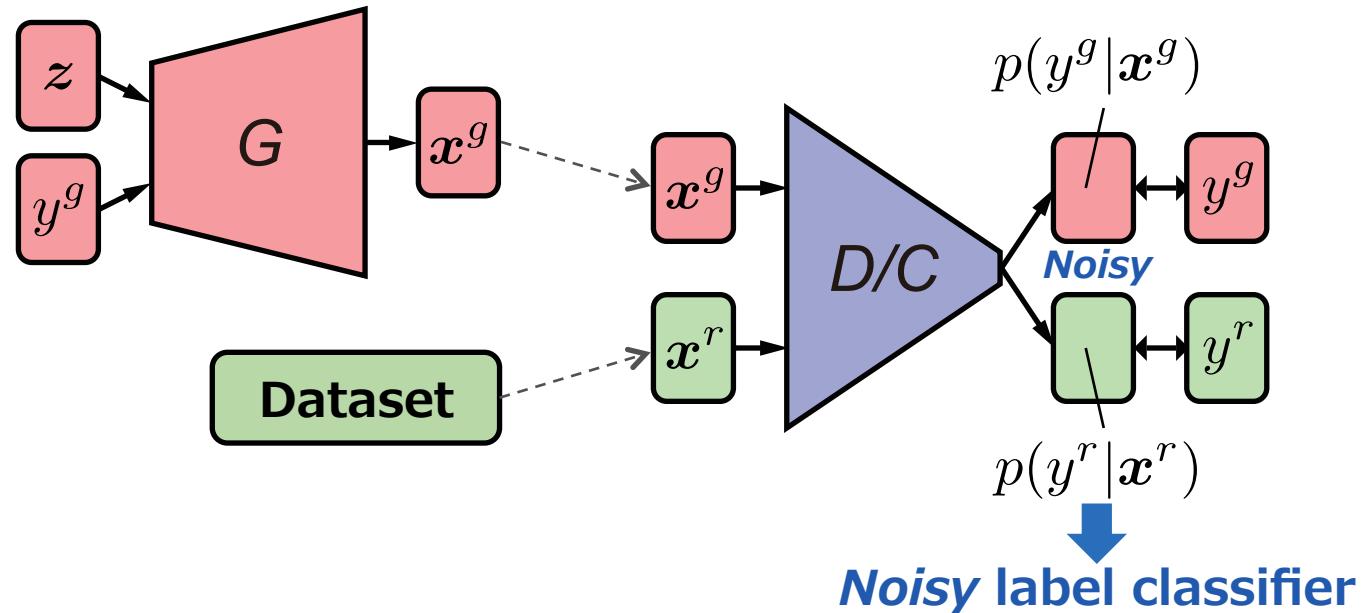
Baseline: AC-GAN

Auxiliary classifier GAN [1]

Generator:

$$G(z, y^g)$$

Discriminator/Classifier: $D(x) / C(y|x)$



Limitation

C can fit **noisy labels** when trained with **noisy labeled data**.

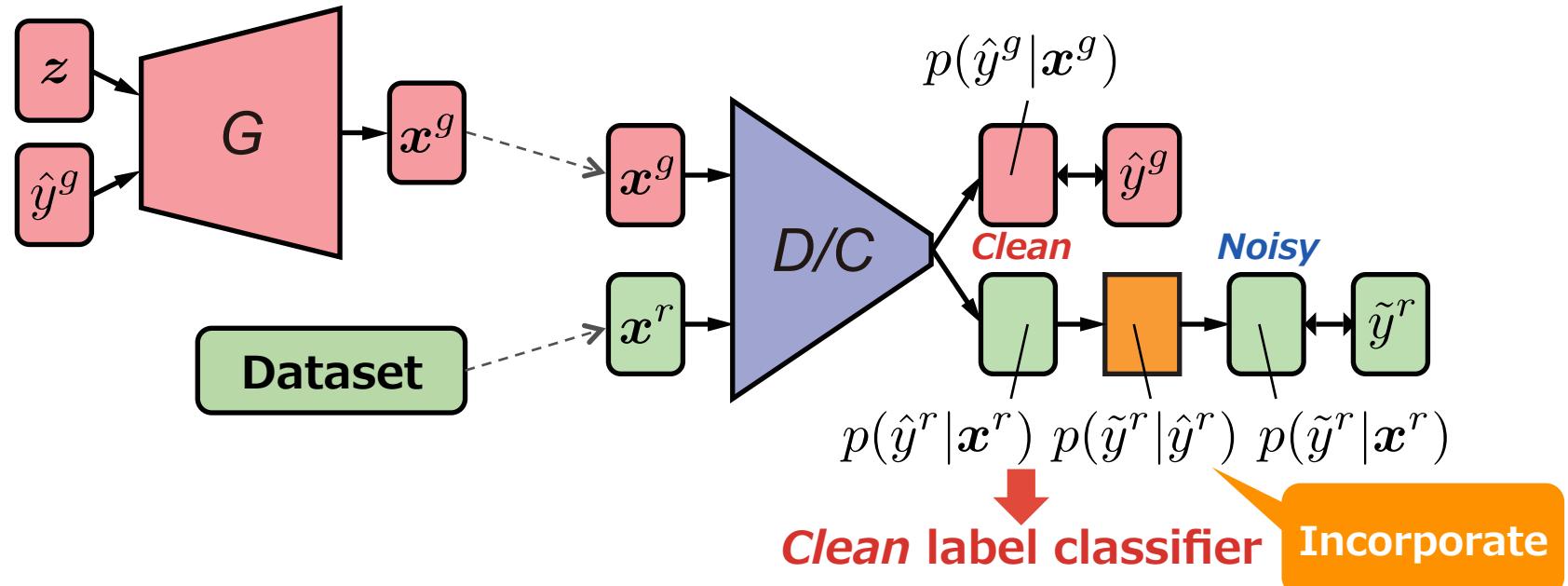
Proposal: rAC-GAN

Label-noise robust auxiliary classifier GAN

Generator:

$$G(z, \hat{y}^g)$$

Discriminator/Classifier: $D(x) / \sum p(\tilde{y}|\hat{y})\hat{C}(\hat{y}|x)$



Solution

We correct the C 's prediction using the **noise transition model** (forward correction [4]).

Baseline: cGAN

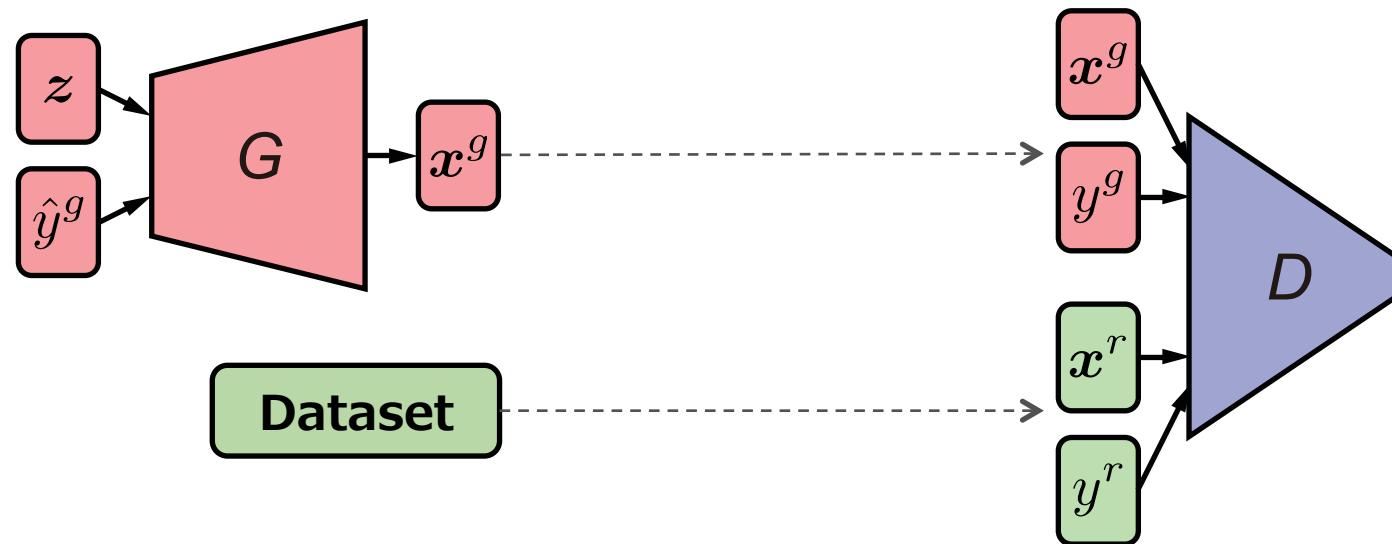
Conditional GAN [2, 3]

Generator:

$$G(z, y^g)$$

Discriminator:

$$D(x, y)$$



Baseline: cGAN

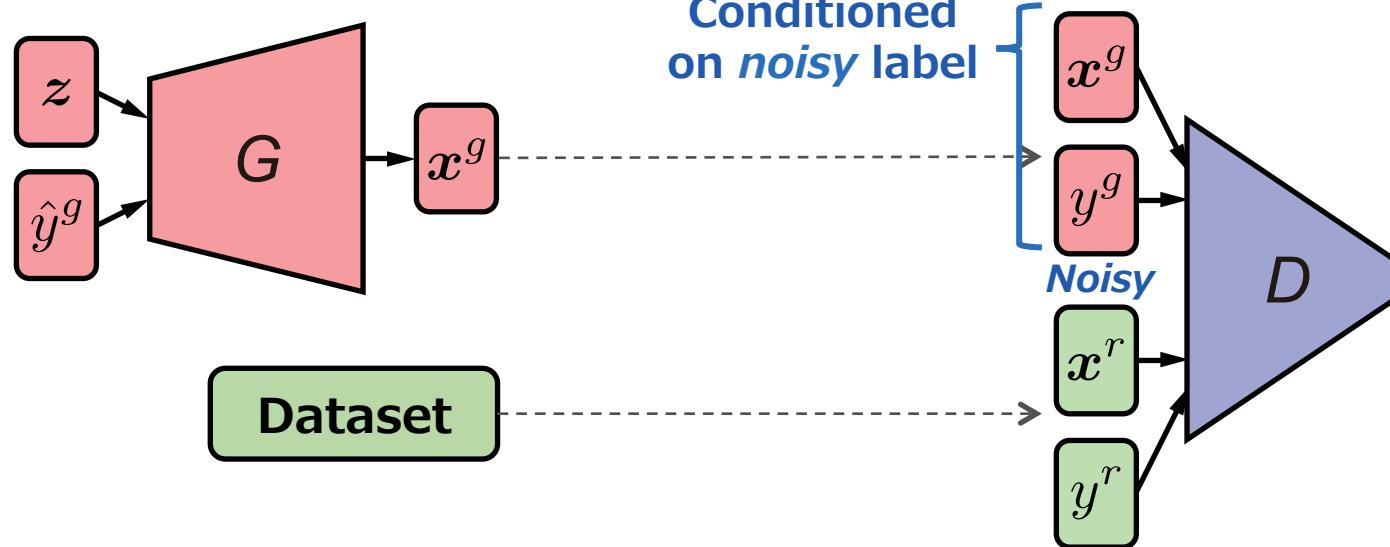
Conditional GAN [2, 3]

Generator:

$$G(z, y^g)$$

Discriminator:

$$D(x, y)$$



Limitation

G is optimized conditioned on **noisy labels** when trained with **noisy labeled data**.

Proposal: rcGAN

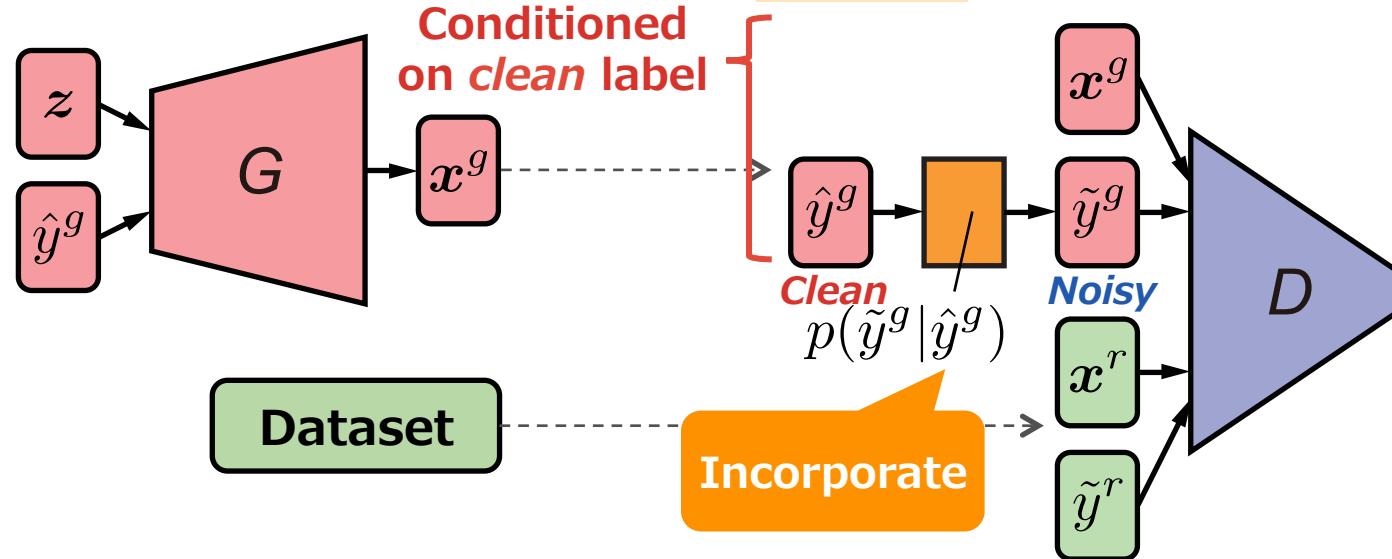
Label-noise robust conditional GAN

Generator:

$$G(z, \hat{y}^g)$$

Discriminator:

$$D(x, \tilde{y}) \quad (\tilde{y}^g \sim p(\tilde{y}|\hat{y}^g))$$



Solution

We correct the D 's input using the **noise transition model**.

Experiment: Comprehensive study

Experimental conditions

Dataset: CIFAR-10 [5], CIFAR-100 [5]

Noise: Symmetric [6], Asymmetric [4] (Noise rate $\in \{0, 0.1, 0.3, 0.5, 0.7, 0.9\}$)

GAN configurations: DCGAN [7], WGAN-GP [8], CT-GAN [9], SN-GAN [10]

Comparison: AC-GAN vs. rAC-GAN, cGAN vs. rcGAN

Evaluation metrics: FID [11], Intra FID [3], GAN-test [12], GAN-train [12]

We tested **336** conditions in total.

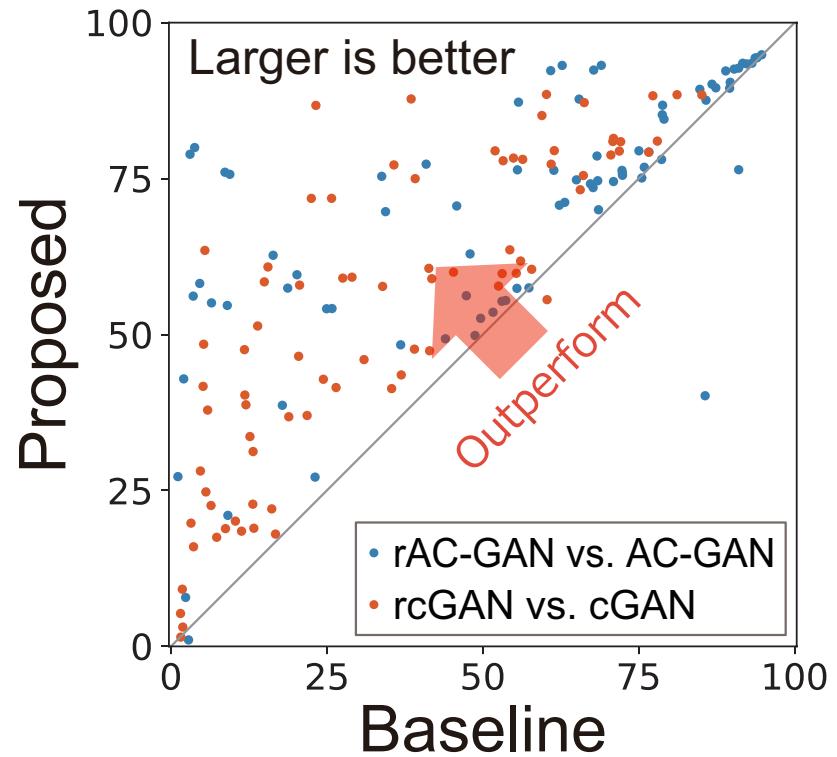
[5] Krizhevsky. 2009. [6] van Rooyen et al. NIPS 2015. [4] Patrini et al. CVPR 2017.

[7] Radford et al. ICLR 2016. [8] Gulrajani et al. NIPS 2017. [9] Wei et al. ICLR 2018. [10] Miyato et al. ICLR 2018.

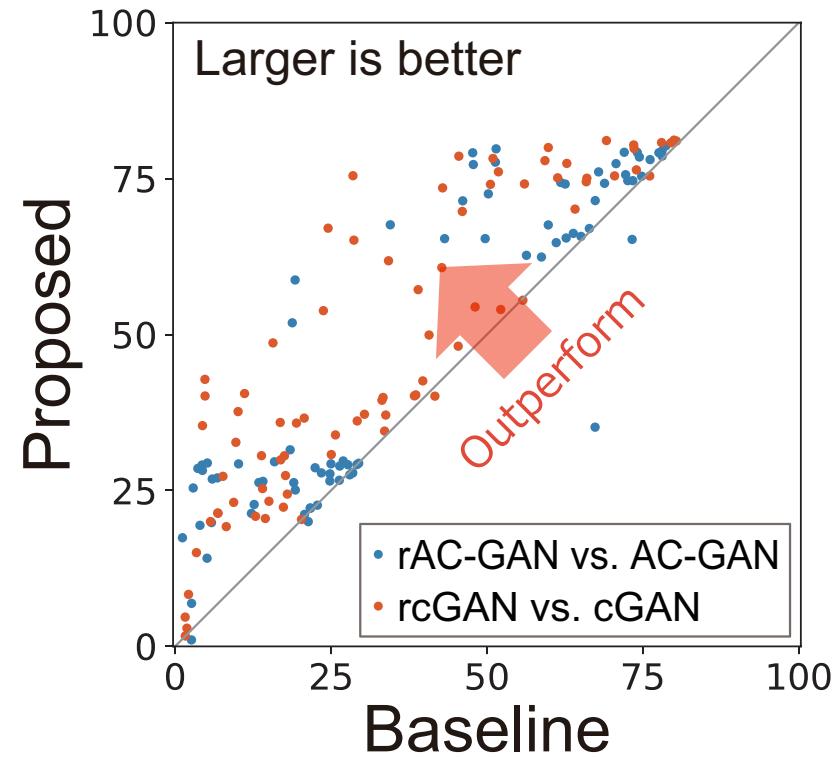
[11] Heusel et al. NIPS 2017. [3] Miyato & Koyama. ICLR 2018. [12] Shmelkov et al. ECCV 2018.

Experiment: Quantitative results

Comparison between the proposed model and the baselines across all the conditions



(a) GAN-test



(b) GAN-train

The proposed models outperform the baselines in most cases.

Experiment: Qualitative results I

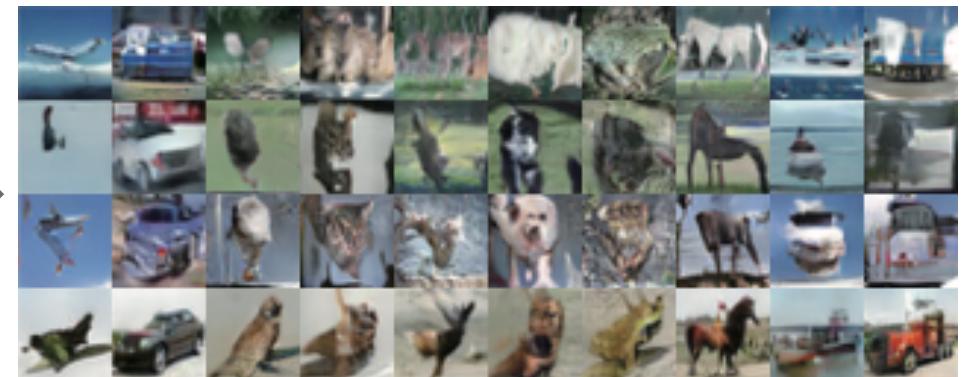
CIFAR-10 symmetric noise (uniform noise)

Baseline



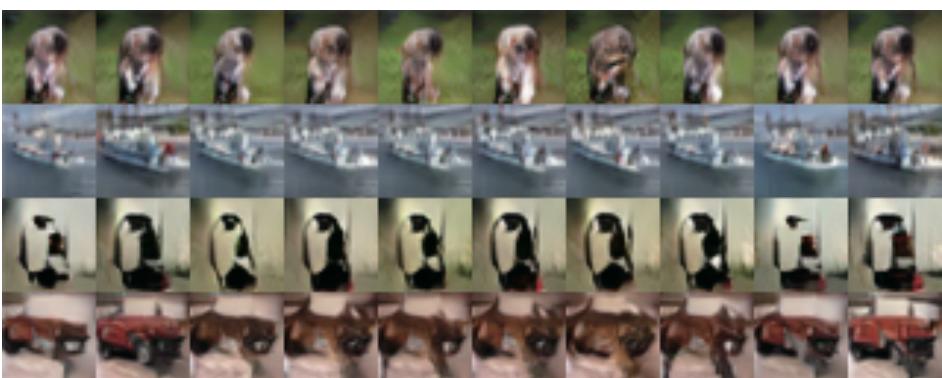
AC-CT-GAN (36.4)

Proposed

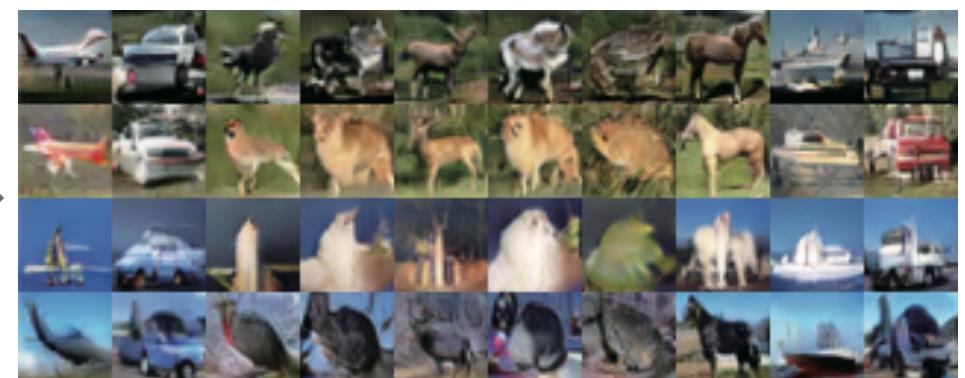


rAC-CT-GAN (30.2)

Significantly
degraded



cSN-GAN (72.0)

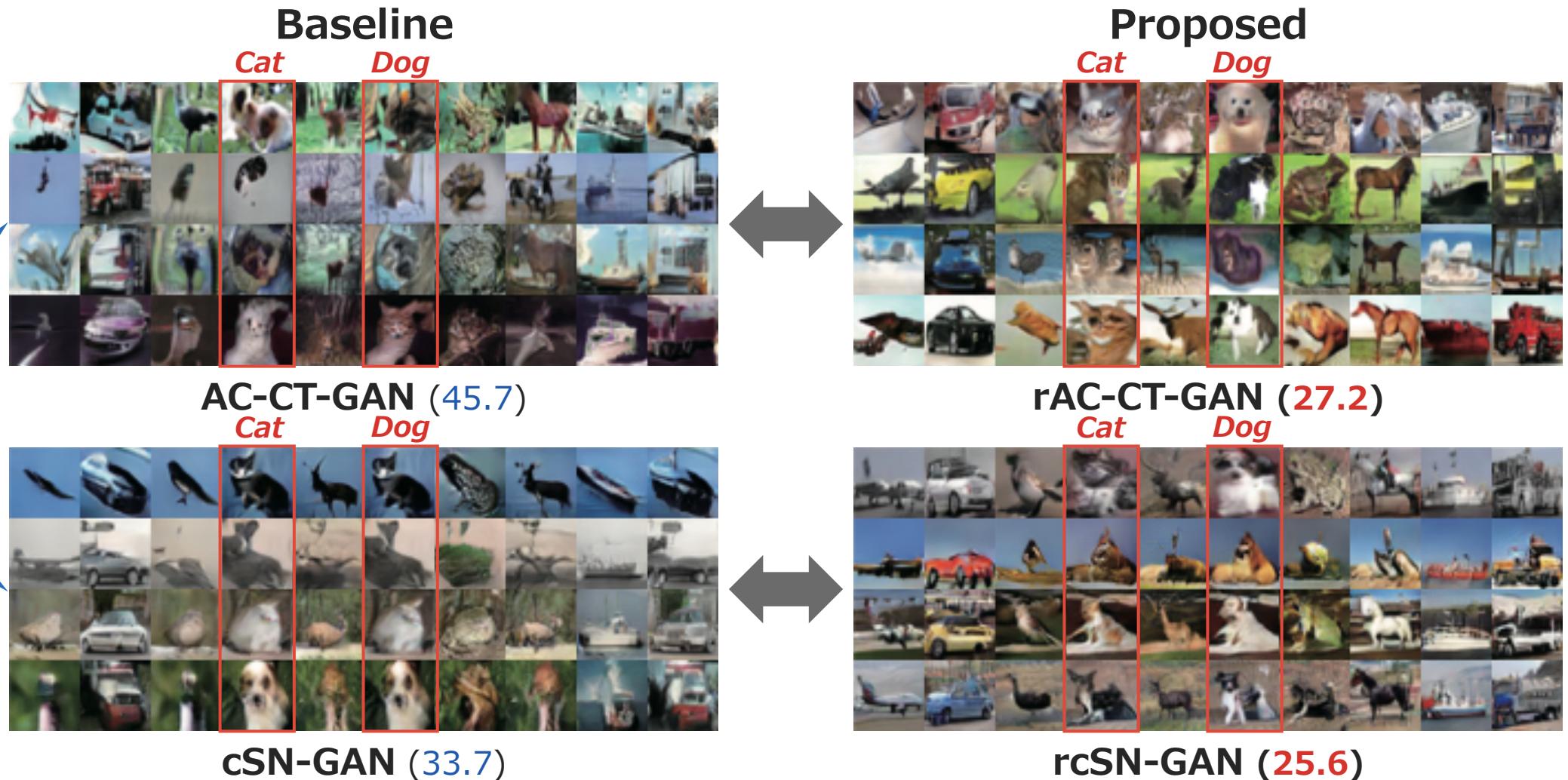


rcSN-GAN (28.6)

The number indicates Intra FID. A smaller value is better.

Experiment: Qualitative results II

CIFAR-10 asymmetric noise (class-dependent noise, e.g., cat \rightleftarrows dog)



The number indicates Intra FID. A smaller value is better.

Further analyses

Effects of estimated noise transition model

We examined the effect when the noise transition model is *estimated from data* [4].

$$\bar{\mathbf{x}}^i = \operatorname{argmax}_{\mathbf{x} \in \mathcal{X}'} C'(\tilde{y} = i | \mathbf{x})$$

$$T'_{i,j} = C'(\tilde{y} = j | \bar{\mathbf{x}}^i)$$

Robust two-step training algorithm [4]

Evaluation of improved technique

We validated the effect of an *improved technique*, which we developed to boost the performance in severely noisy setting.

$$\mathcal{L}_{\text{MI}} = \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z}), \hat{y}^g \sim p(\hat{y})} [-\log Q(\hat{y} = \hat{y}^g | G(\mathbf{z}, \hat{y}^g))]$$

Loss for improving the performance



Qualitative results on Clothing1M

Evaluation on real-world noise

We tested on Clothing1M [13], which includes *real-world noisy labeled data*.

Thank you!

Our code is publicly available at <https://github.com/takuhirok/rGAN/>

Poster

Session: Synthesis

#: 133

Time: Tuesday 15:20-18:00

