



## Introduction

### Objective: Label-noise robust image generation

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

(a) Clean labeled data

(b) Noisy labeled data



Unobservable

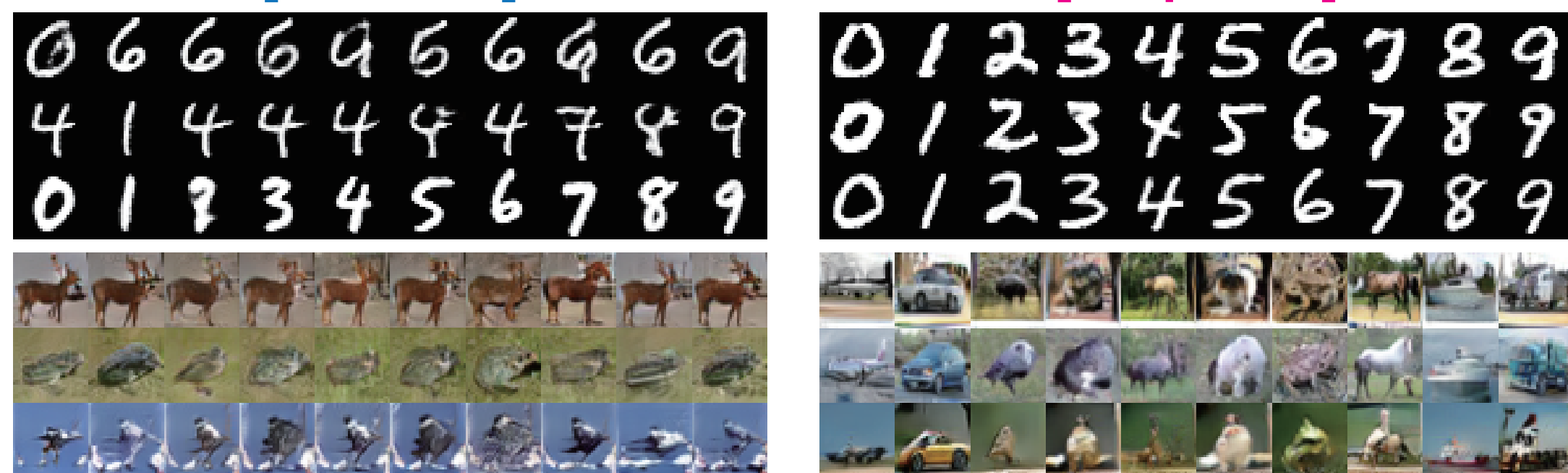
Observable

### Challenge and contribution

- Naïve conditional generative models construct a generator conditioned on **observable (noisy) labels** (c).
- Our proposed rGANs (label-noise robust GANs) can construct a generator conditioned on **clean labels** (d) even when trained with **noisy labeled data** (b).

(c) cGAN trained with (b)  
[Baseline]

(d) rcGAN trained with (b)  
[Proposed]

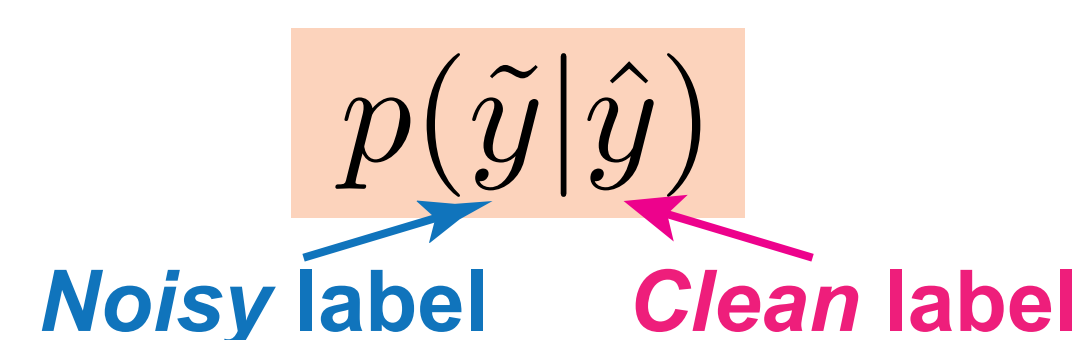


Fits observable (noisy) labels

Robust to label noise

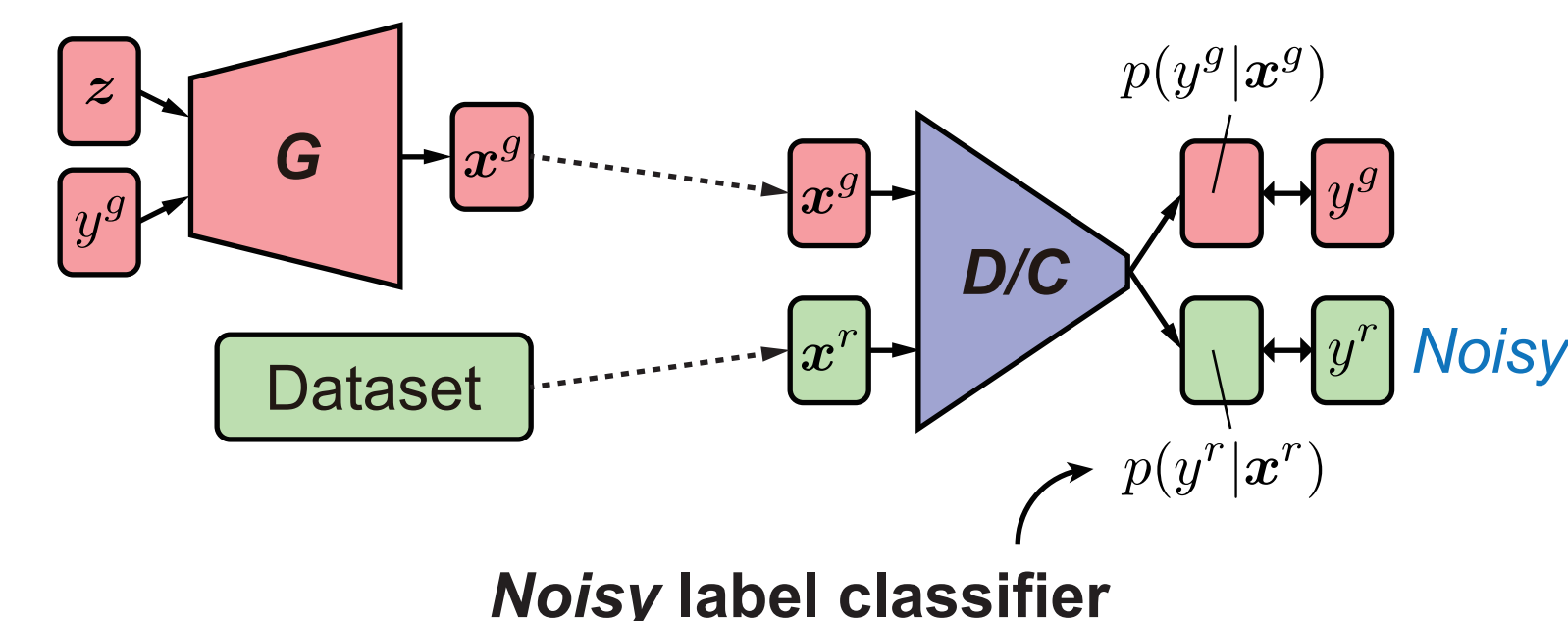
## Key idea

### Incorporation of noise transition model



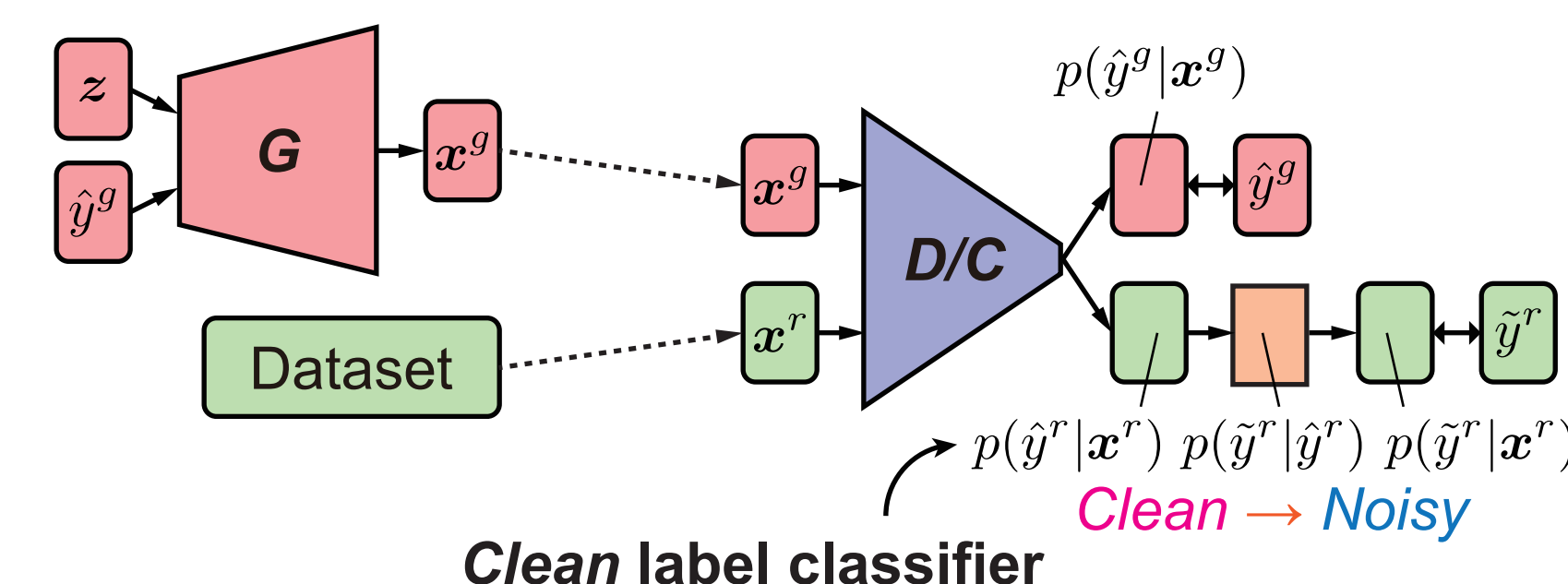
## Method

### Baseline 1: AC-GAN (auxiliary classifier GAN) [Odena et al. 2017]



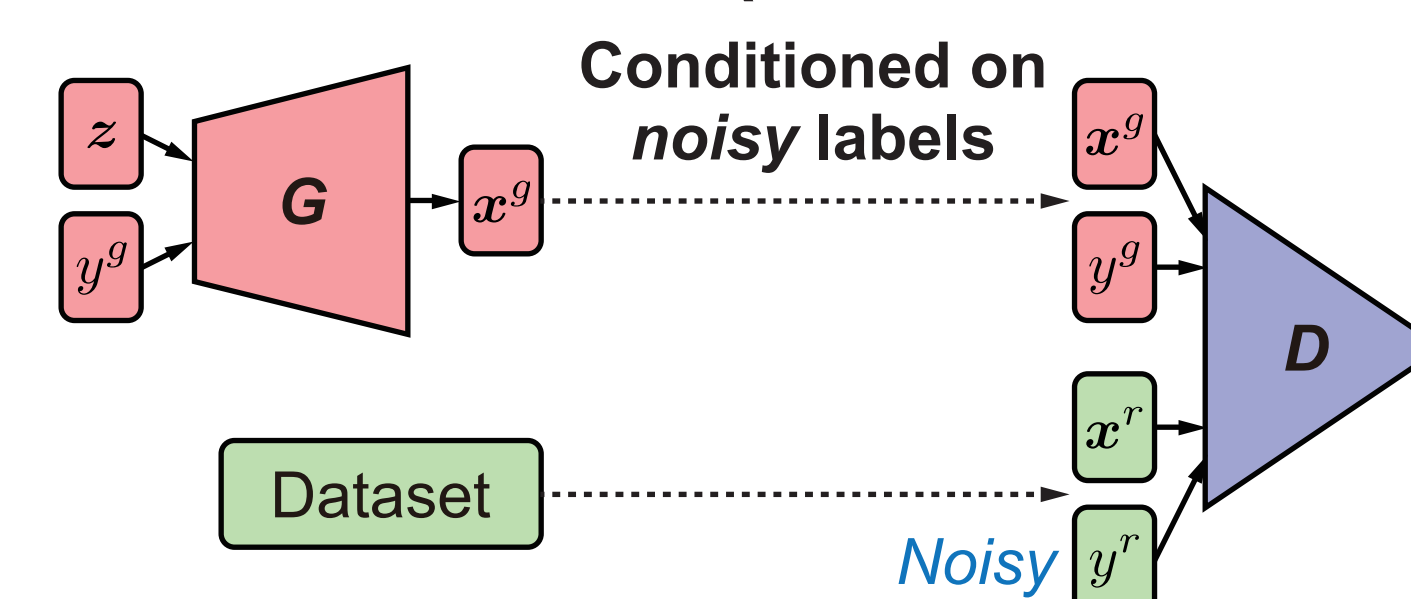
Limitation: **C** can fit **noisy labels** when trained with **noisy labels**.

### Proposal 1: rAC-GAN (label-noise robust AC-GAN)



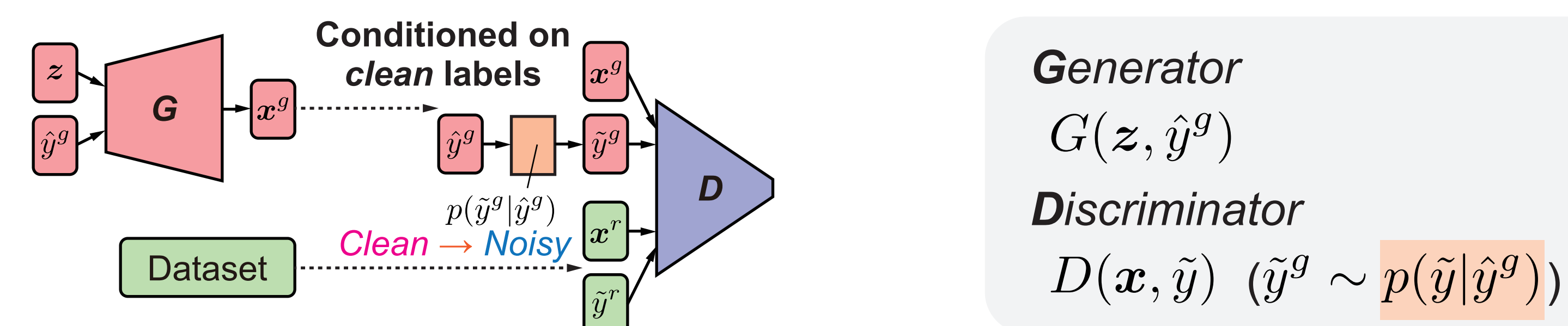
Solution: We correct **C** prediction using the **noise transition model**.

### Baseline 2: cGAN (conditional GAN) [Mirza & Osindero. 2014, Miyato & Koyama. 2018]



Limitation: **G** is optimized conditioned on **noisy labels** when trained with **noisy labels**.

### Proposal 2: rcGAN (label-noise robust cGAN)



Solution: We correct **D** input using the **noise transition model**.

## Experiments

### Comprehensive study (336 conditions were tested in total)

Dataset: CIFAR-10 and CIFAR-100

Noise: Symmetric noise and asymmetric noise (noise rate  $\mu \in \{0, 0.1, 0.3, 0.5, 0.7, 0.9\}$ )

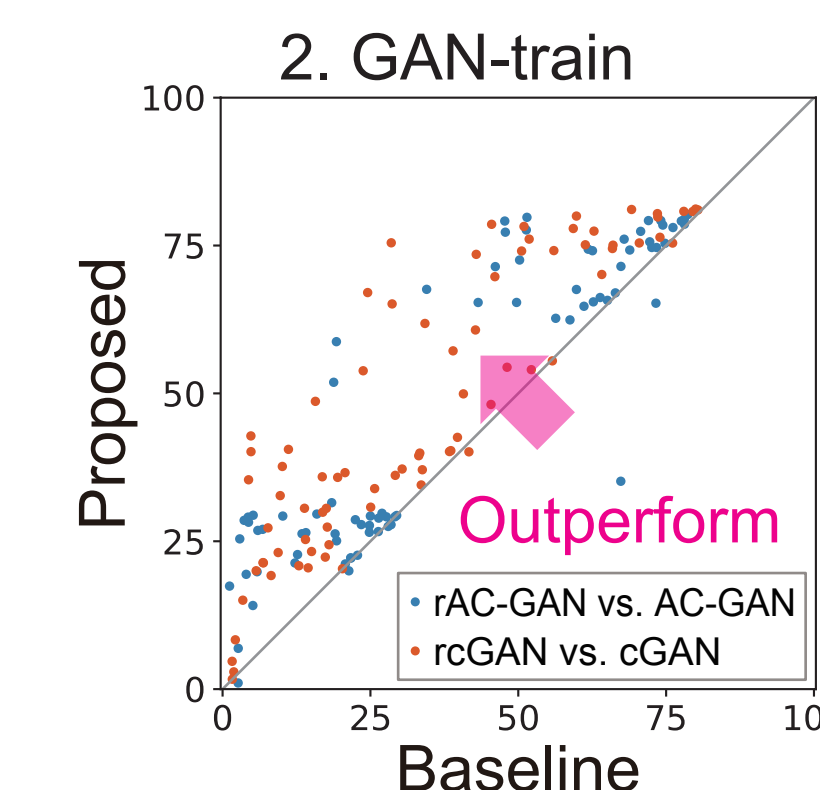
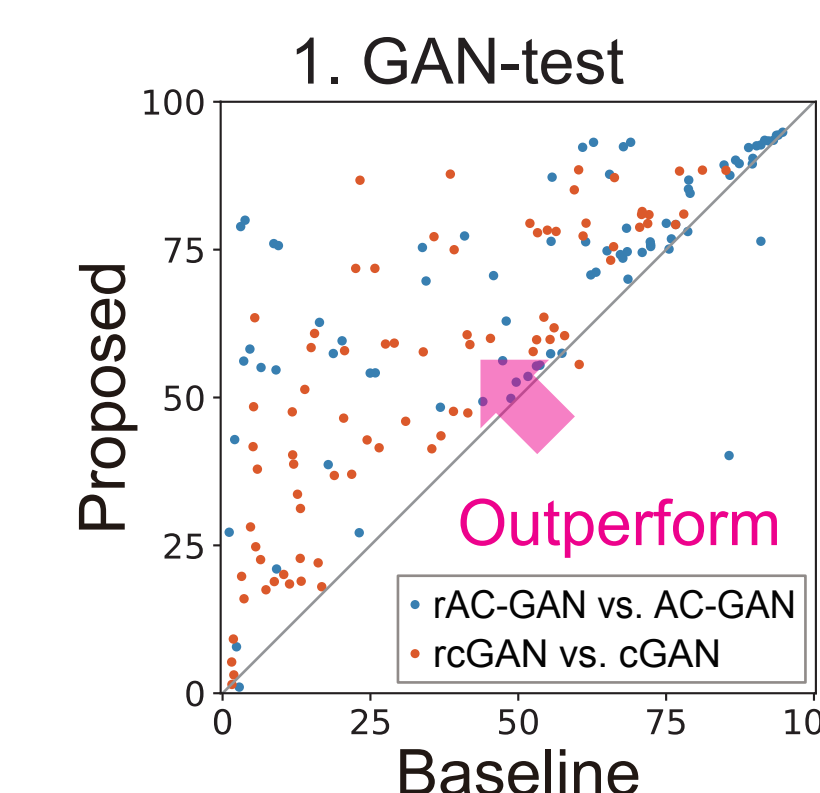
GAN configuration: DCGAN, WGAN-GP, CT-GAN, and SN-GAN

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

Evaluation metrics: FID, Intra FID, GAN-test, and GAN-train

### Quantitative results

Comparison across all conditions



### Qualitative results

[Baseline]

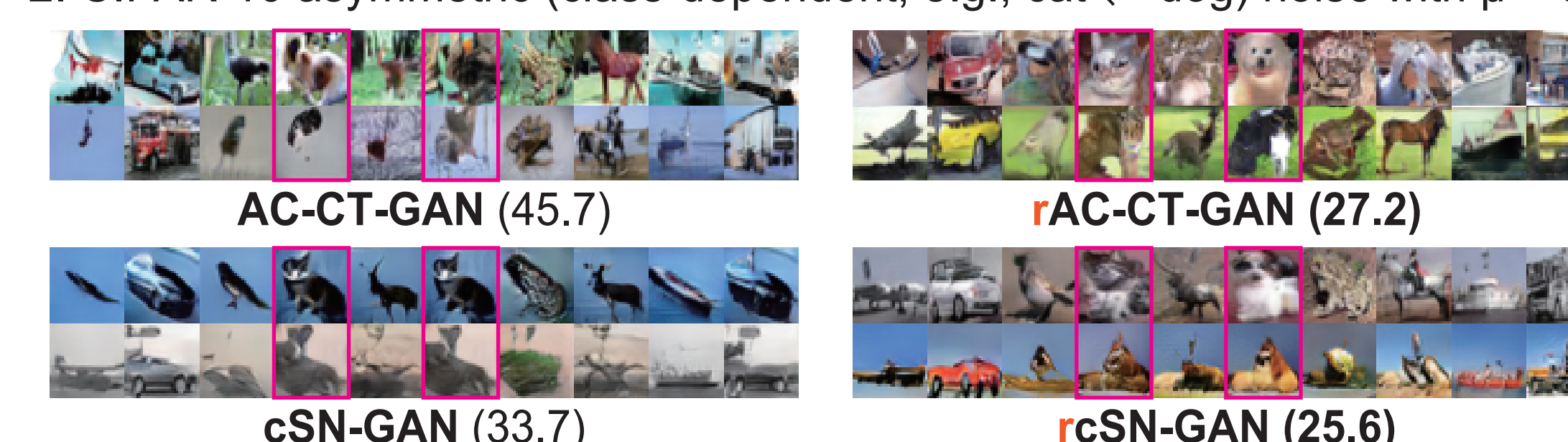
[Proposed]

1. CIFAR-10 symmetric (uniform) noise with  $\mu = 0.7$



Failed to learn disentangled representations

2. CIFAR-10 asymmetric (class-dependent; e.g., cat  $\rightleftharpoons$  dog) noise with  $\mu = 0.7$



Confused between flipped classes

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

### Further analyses (see paper for details)

#### Effects of estimated noise transition model

We examined the effect when the noise transition model is estimated from data [Patrini et al. 2017].

#### Evaluation of improved technique

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

#### Evaluation on real-world noise

We tested rGANs in a real-world noise setting using Clothing1M [Xiao et al. 2015], which includes real-world noisy labeled data.

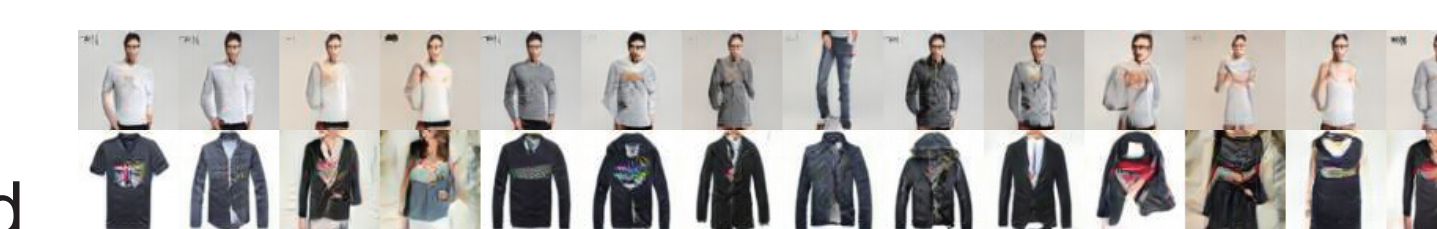
$$\bar{x}^i = \operatorname{argmax}_{x \in \mathcal{X}'} C'(\tilde{y} = i|x)$$

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

Robust two-step training algorithm

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

Mutual information regularization



Qualitative results on Clothing1M