

Robustness of Conditional GANs to Noisy Labels

Spotlight presentation, NeurIPS 2018

Kiran K. Thekumparampil¹ Ashish Khetan¹
Zinan Lin² Sewoong Oh¹

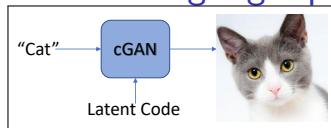
¹University of Illinois at Urbana-Champaign

²Carnegie Mellon University

Poster #5, Tue, Dec 4 2018

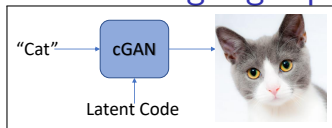
Conditional GAN (cGAN) is vital for achieving high quality

- **Input:** Labeled real samples (X, Y)
- **Output:** Fake samples for label Y



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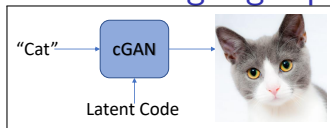
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[Brock et al. 2018]

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- **Visual quality:**



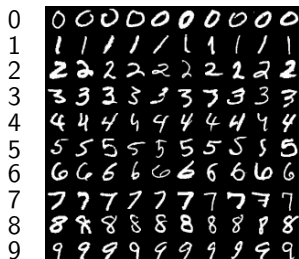
[<https://github.com/tensorflow/models/tree/master/research/gan>]

Conditional GAN is sensitive to noise in labels

cGAN trained with noisy labels produces samples

- that are **biased**, generating examples from wrong classes, and,
- of **lower quality** (red boxes).

label



real data

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0	1	4	0	1	0	4	5	9	2	7
1	1	1	2	9	0	5	7	1	5	1
2	8	2	2	0	1	4	5	5	2	1
3	3	3	3	1	1	6	2	3	9	3
4	4	6	5	4	4	4	1	4	4	4
5	2	5	5	7	2	5	8	1	4	3
6	3	6	5	1	4	7	7	4	3	6
7	0	7	6	2	7	1	7	3	7	7
8	6	8	2	0	8	1	8	9	8	8
9	0	1	9	5	9	0	9	4	3	4

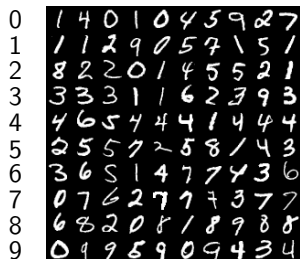
noisy real data

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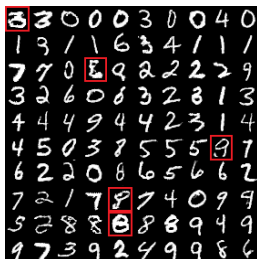
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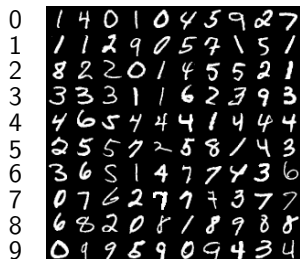
standard cGAN

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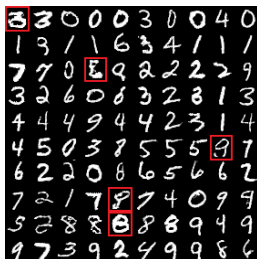
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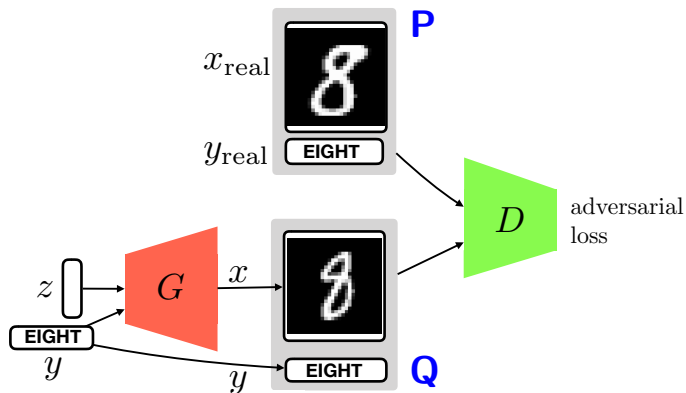


standard cGAN



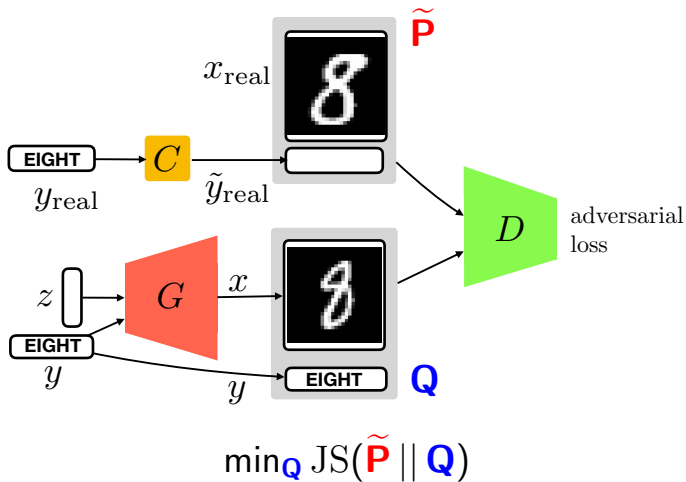
our RCGAN

Conditional GAN (cGAN)

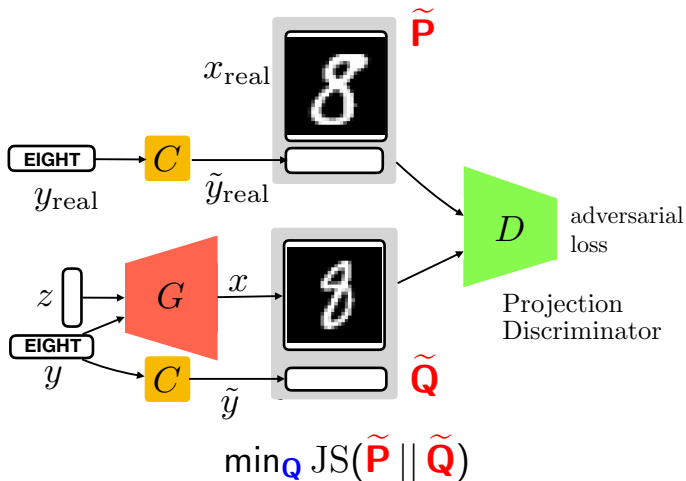


$$\min_Q \text{JS}(P \parallel Q)$$

Conditional GAN under noisy labeled data



Robust Conditional GAN (RCGAN) Architecture



[Bora et al. 2018, Miyato et al. 2018, Sukhbaatar et al. 2015]

Minimizing noisy divergence minimizes true divergence

Let $\tilde{P}$ & $\tilde{Q}$ be the noisy labeled versions of P & Q .

Theorem 1 (Population-level Analysis)

$$\left. \begin{aligned} \text{TV}(\tilde{P}, \tilde{Q}) &\leq \text{TV}(P, Q) \leq M_C \text{TV}(\tilde{P}, \tilde{Q}) \\ \text{JS}(\tilde{P} \parallel \tilde{Q}) &\leq \text{JS}(P \parallel Q) \leq M_C \sqrt{8 \text{JS}(\tilde{P} \parallel \tilde{Q})} \end{aligned} \right\} \Rightarrow \tilde{Q} = \tilde{P} \Rightarrow Q = P$$

where TV : Total Variation, JS : Jensen-Shannon divergence and $M_C \triangleq \max_i \sum_j |(C^{-1})_{ij}|$.

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Neural Network Distance ($d_{\mathcal{F}}$) w.r.t a class of parametric discriminator functions $\mathcal{F}$ is known to generalize [Arora et al. 2017]

Minimizing noisy divergence minimizes true divergence

Let $\tilde{P}_n$ & $\tilde{Q}_n$ be the empirical noisy real and generated distributions.

Theorem 2 (Finite Sample Analysis)

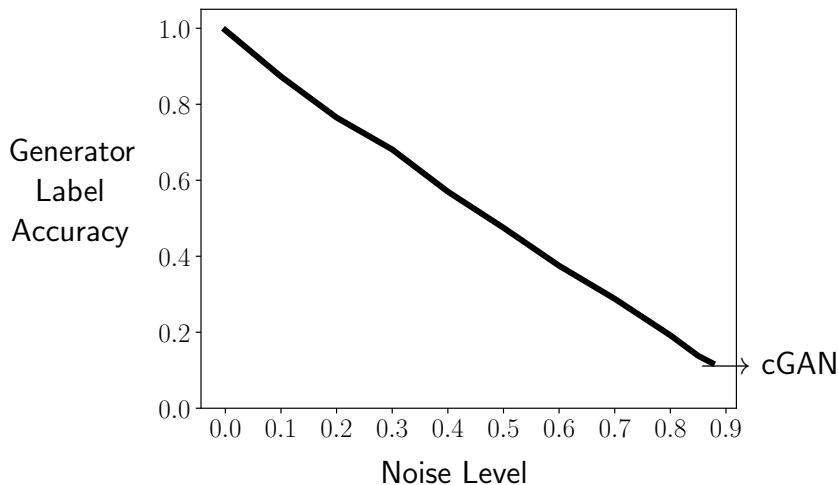
If $\mathcal{F}$ satisfies **inclusion condition**, then $\exists c > 0$ such that

$$d_{\mathcal{F}}(\tilde{P}_n, \tilde{Q}_n) - \epsilon \leq d_{\mathcal{F}}(P, Q) \leq M_C (d_{\mathcal{F}}(\tilde{P}_n, \tilde{Q}_n) + \epsilon)$$

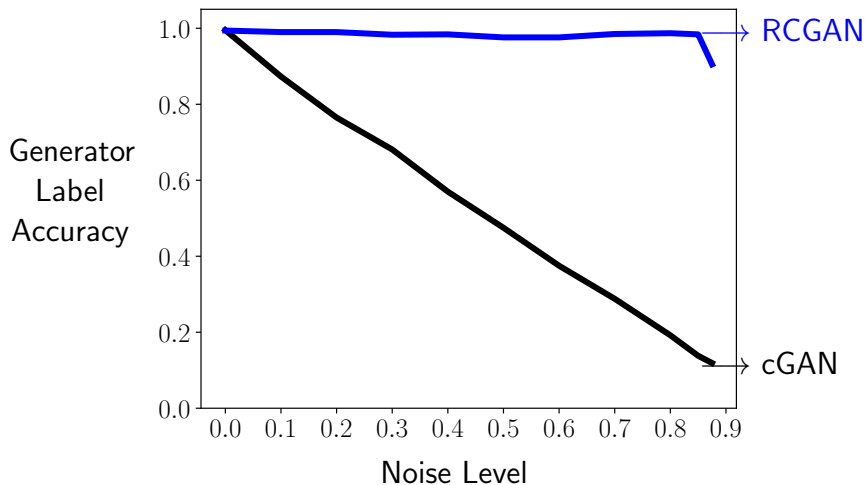
with probability at least $1 - e^{-p}$ for any $\epsilon > 0$ and $n \geq cp \log(pL/\epsilon) / \epsilon^2$
when $\mathcal{F}$ is L -Lipschitz in p parameters

Projection Discriminator satisfies **inclusion condition**

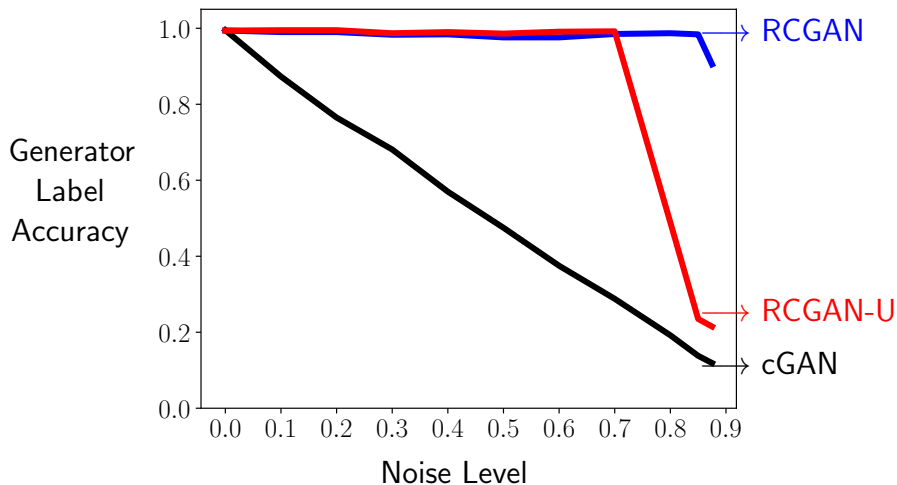
RCGAN generates correct class (MNIST)



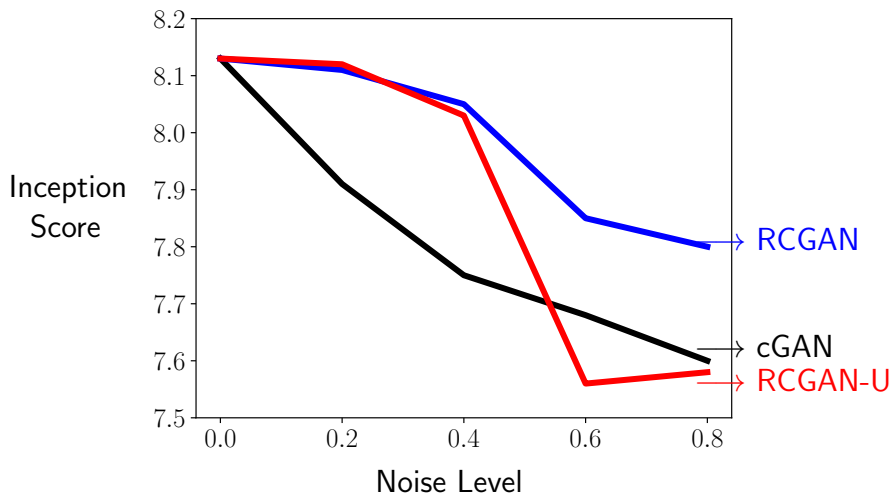
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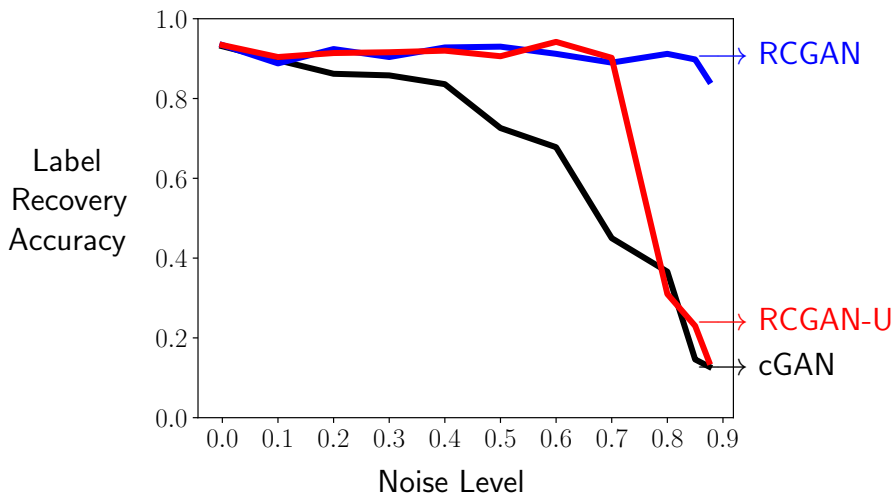
RCGAN generates correct class (MNIST)



RCGAN improves quality of samples (CIFAR-10)



RCGAN can correct noisy training labels (MNIST)



Thank you

Poster #5, Tue, Dec 04

<https://github.com/POLane16/Robust-Conditional-GAN>



[Arora 2015] S. Arora, R. Ge, Y. Liang, T. Ma, and Y. Zhang. Generalization and equilibrium in generative adversarial nets (GANs), *ICML 2018*.

[Bora 2018] A. Bora, E. Price, and A. G. Dimakis. AmbientGAN: Generative models from lossy measurements, *ICLR, 2018*.

[Brock 2018] A. Brock, J. Donahue, and K. Simonyan. Large scale gan training for high fidelity natural image synthesis, *arXiv preprint arXiv:1809.11096*.

[Miyato 2018] T. Miyato, and M. Koyama. cGANs with projection discriminator. *ICLR, 2018*.

[Sukhbaatar 2015] S. Sukhbaatar, J. Bruna, M. Paluri, L. Bourdev, and R. Fergus. Training convolutional networks with noisy labels. *In ICLR, Workshop, 2015*.