



Twin Auxiliary Classifiers GAN

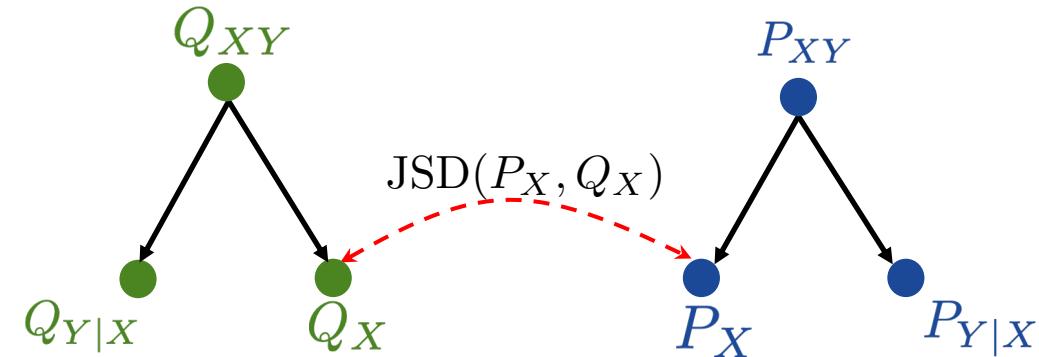
NeurIPS 2019

AC-GAN: Density Matching Point of View

$$\min_{G,C} \max_D \mathcal{L}_{GAN}(G, D)$$

$$- \mathbb{E}_{(X,Y) \sim P_{XY}} [\log C(X, Y)]$$

$$- \mathbb{E}_{Z \sim P_Z, Y \sim P_Y} [\log(C(G(Z, Y), Y))]$$

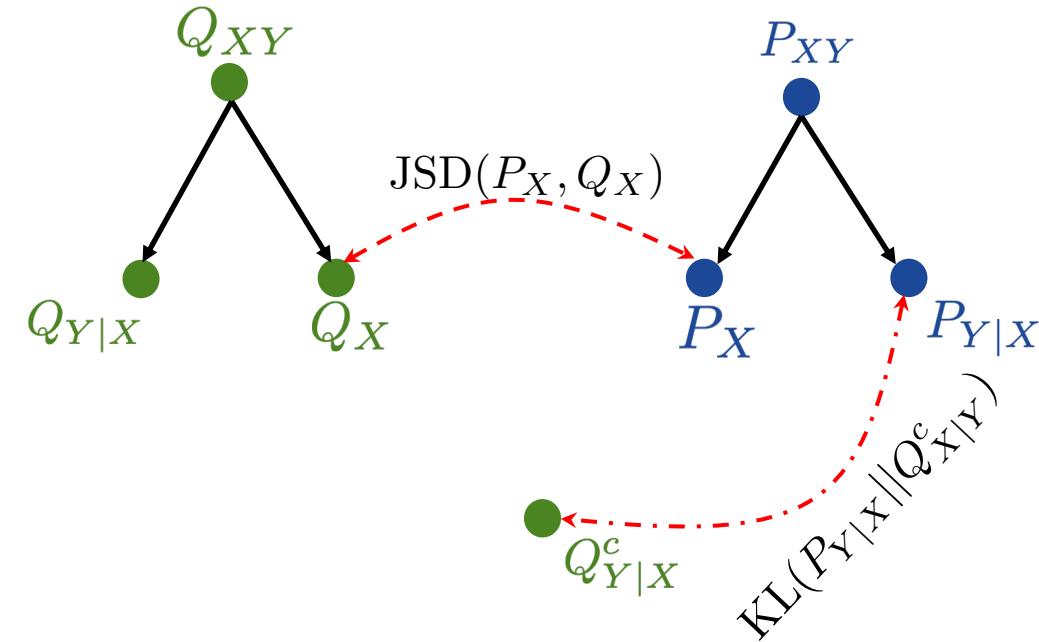


AC-GAN: Density Matching Point of View

$$\min_{G,C} \max_D \mathcal{L}_{GAN}(G, D)$$
$$- \mathbb{E}_{(X,Y) \sim P_{XY}} [\log C(X, Y)] - H_P(Y|X)$$

This is a constant
(It doesn't matter!)

$$- \mathbb{E}_{Z \sim P_Z, Y \sim P_Y} [\log(C(G(Z, Y), Y))]$$

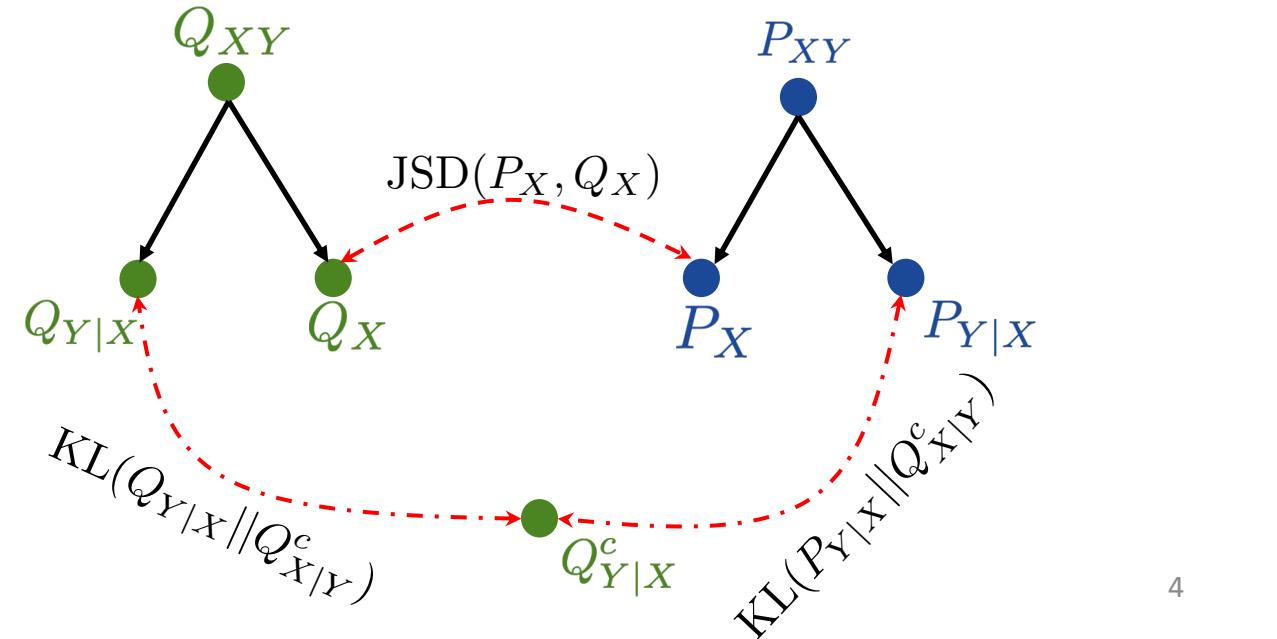


AC-GAN: Density Matching Point of View

$$\min_{G,C} \max_D \mathcal{L}_{GAN}(G, D)$$

$$- \mathbb{E}_{(X,Y) \sim P_{XY}} [\log C(X, Y)] - H_P(Y|X) \quad \text{This is a constant
(It doesn't matter!)}$$

$$- \mathbb{E}_{Z \sim P_Z, Y \sim P_Y} [\log(C(G(Z, Y), Y))] - H_Q(Y|X) \quad \text{This is NOT a constant b/c of G}$$



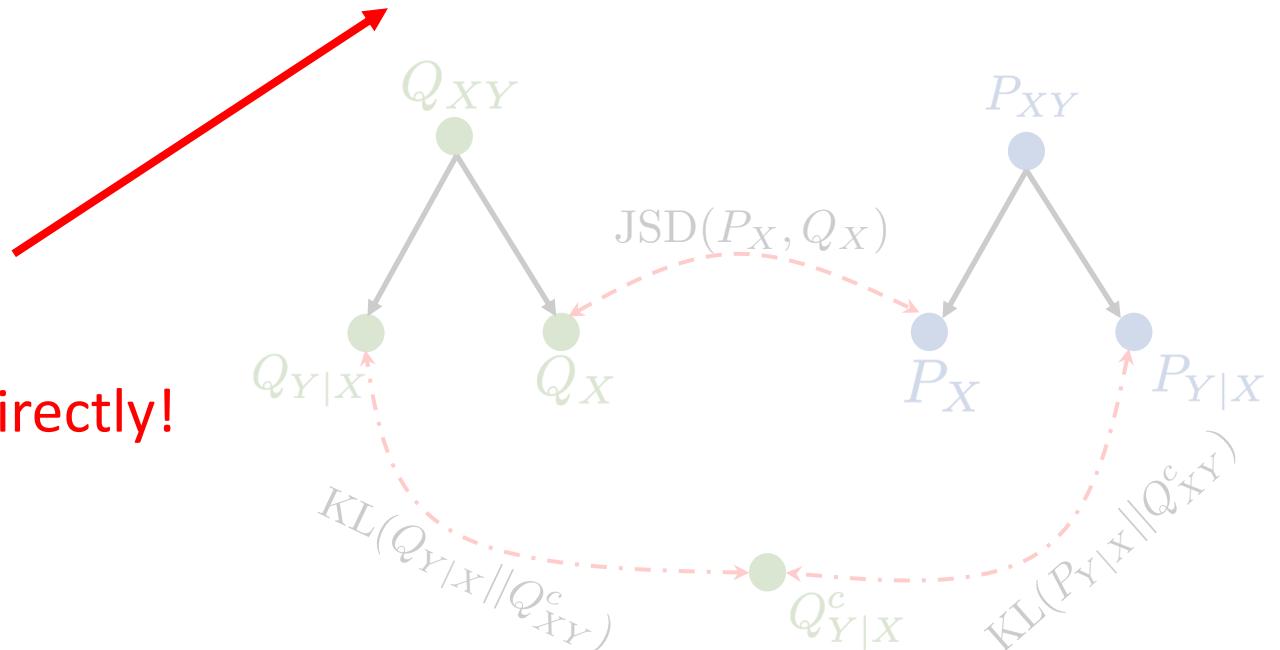
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(Missing term!)}$$

Missing term in AC-GAN
Very difficult to estimate directly!



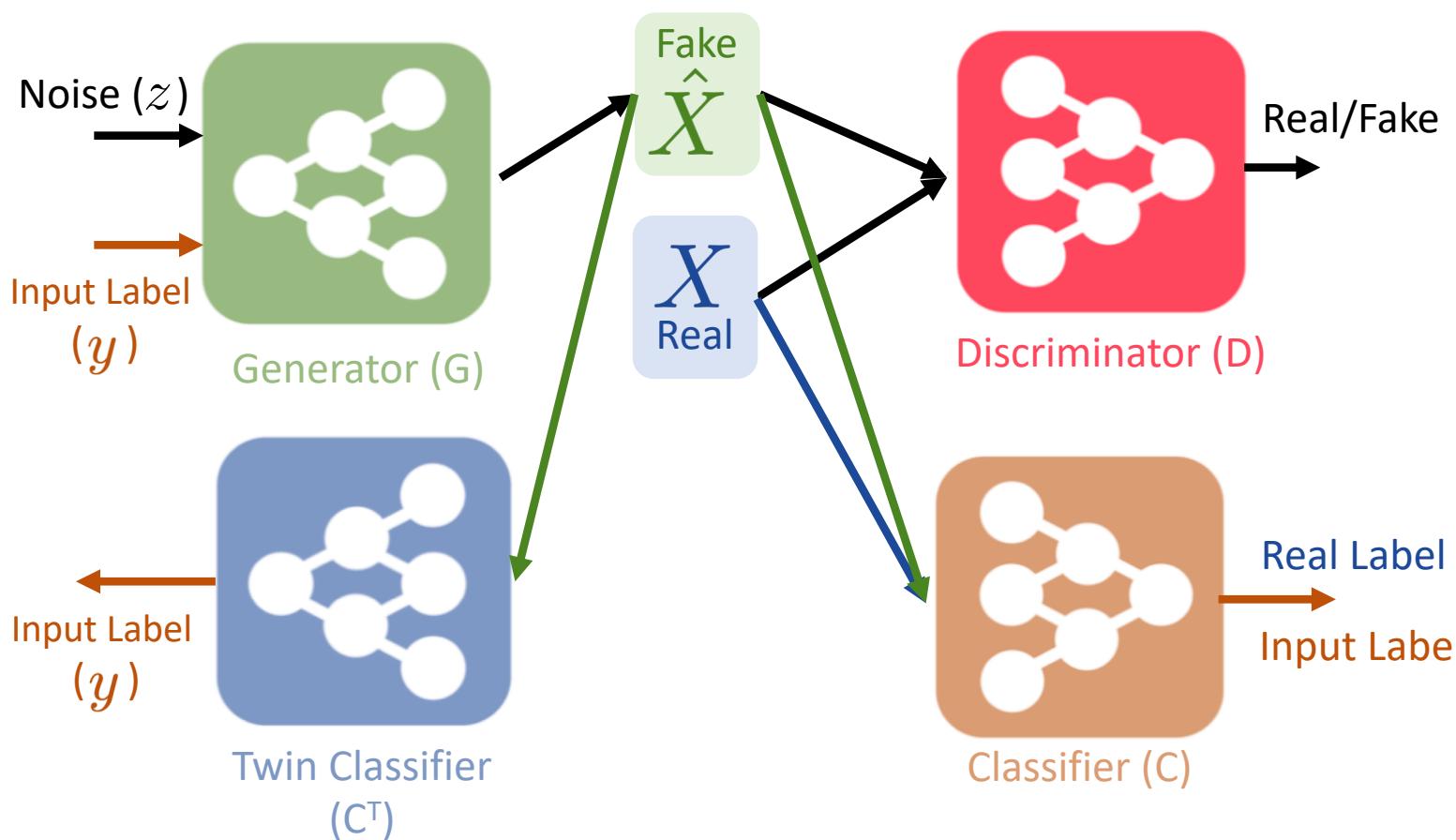
Conversion to a Min-Max Game

Proposition:

- If $p(Y)$ is a uniform distribution, the following are equivalent:
 - Maximizing $H_Q(Y|X)$
 - Minimizing $I_Q(X, Y)$
 - Minimizing $JSD(Q_{X|Y=1}, Q_{X|Y=2}, \dots, Q_{X|Y=K})$

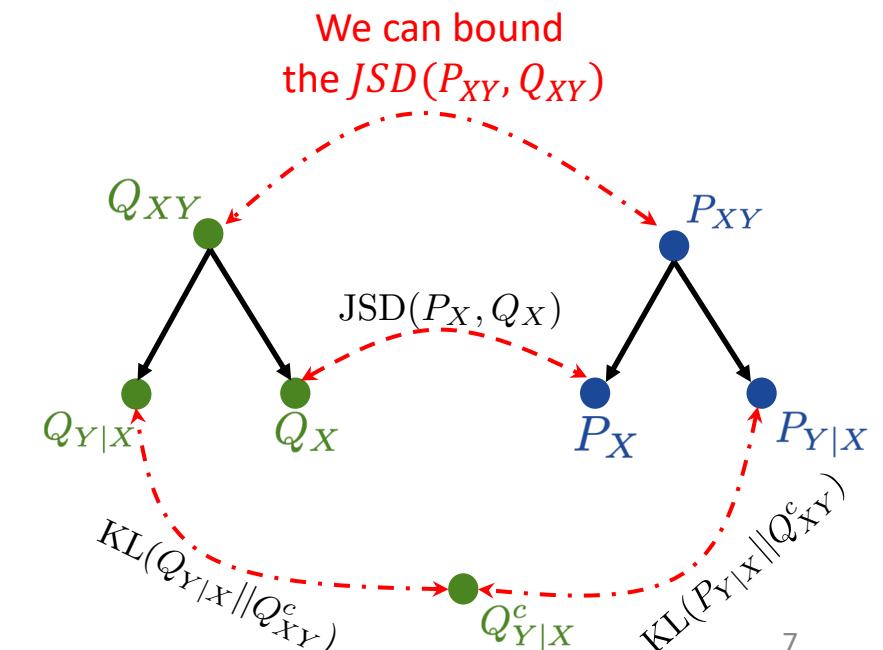
A Min-Max game can be introduced!

Twin Auxiliary Players



- The twin player (C^T) only works on “Fake” samples.
- The Generator (G) tries to make fake samples indistinguishable for C^T .
- Minimax is achieved at:

$$JSD(Q_{X|Y=1}, Q_{X|Y=2}, \dots, Q_{X|Y=K}) = 0$$

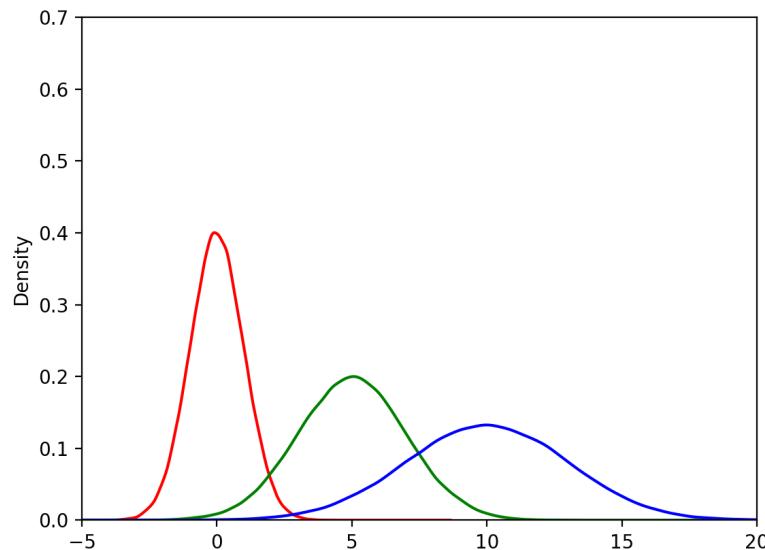


Outlines

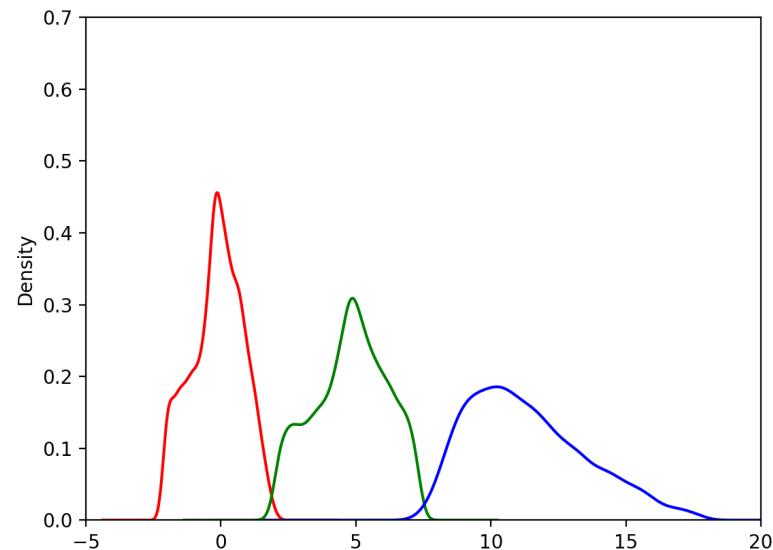
- Review of GANs and conditional-GANs
- Issues with ACGAN
- Twin Auxiliary Classifiers GANs
- **Results**
- Applications (time permits)

Going Back to the 1D Case

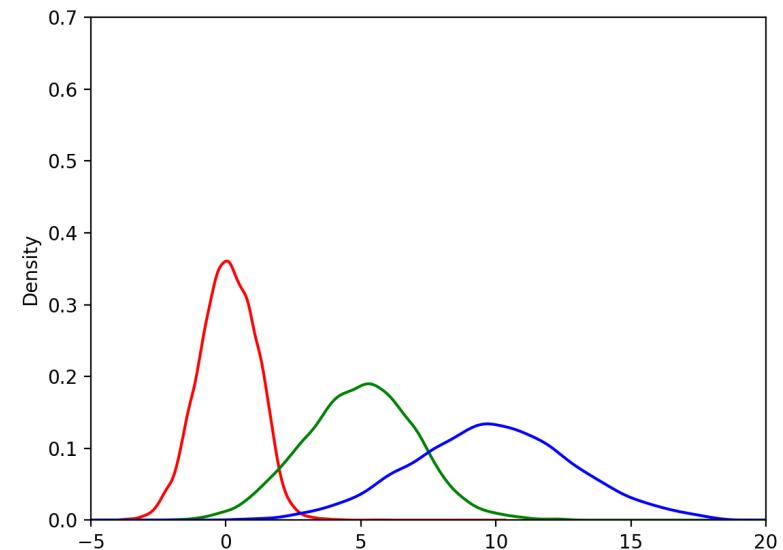
True Distribution



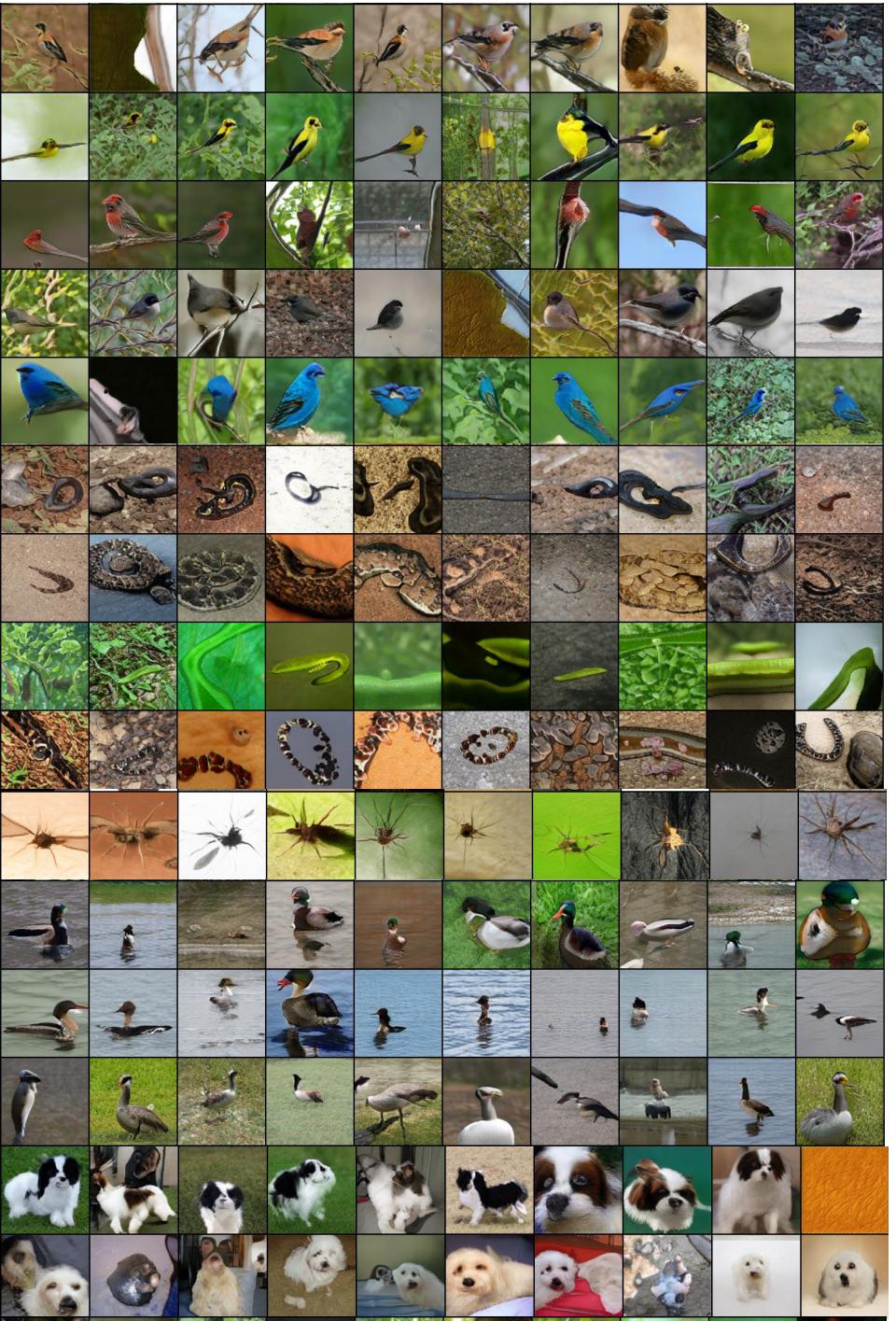
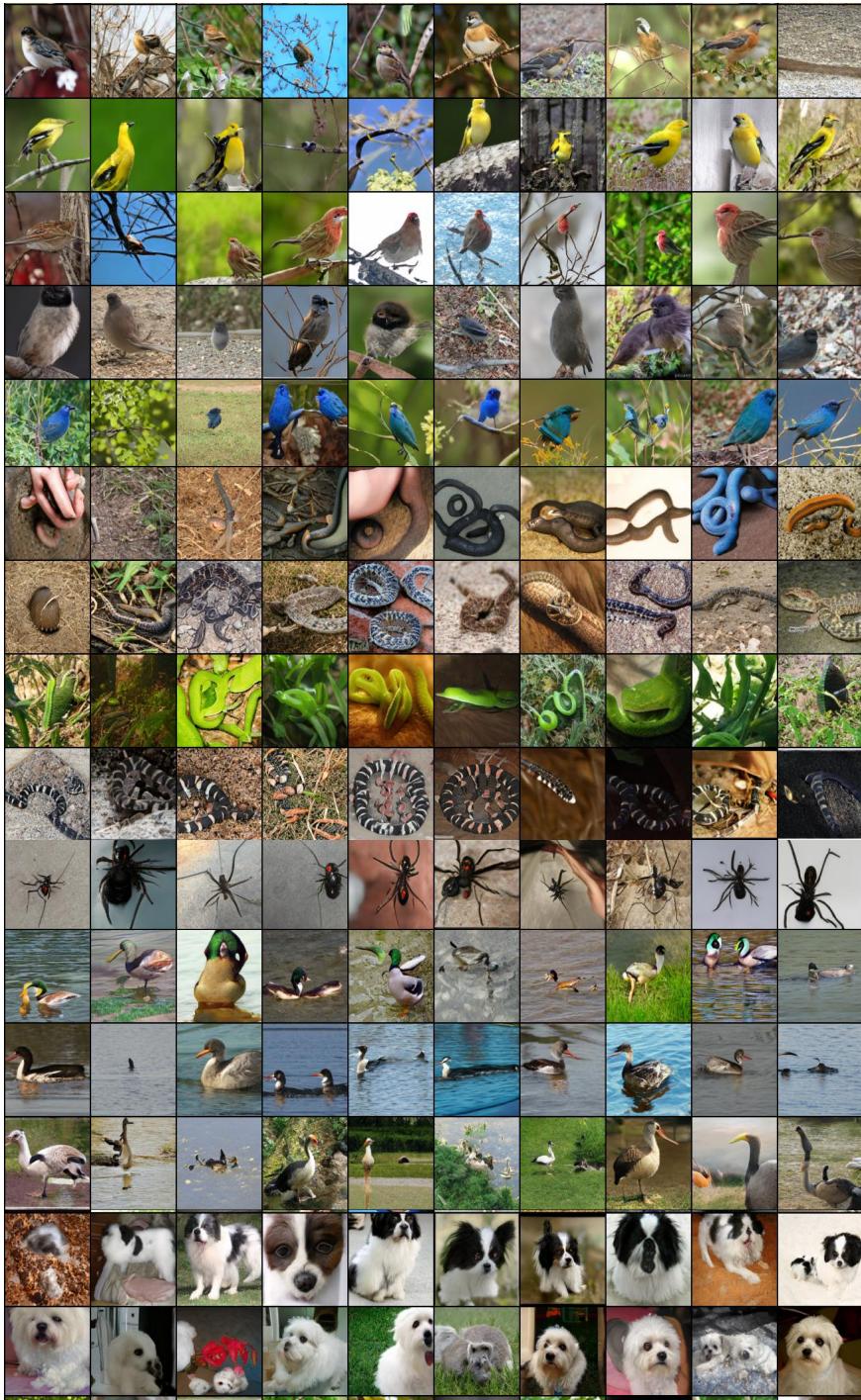
AC-GAN



Our Method



TAC-GAN (Ours)



projection cGAN

TAC-GAN (Ours)



Projection cGAN



Quantitative Comparison

Methods	AC-GAN ($\lambda_c = 1$)			TAC-GAN (Ours) ($\lambda_c = 1$)			Projection cGAN		
	IS ↑	FID ↓	LPIPS ↑	IS ↑	FID ↓	LPIPS ↑	IS ↑	FID ↓	LPIPS ↑
CIFAR100	5.37 ± 0.064	82.45	0.003	9.34 ± 0.077	7.22	0.165	9.56 ± 0.133	8.92	0.169
ImageNet1000	7.26 ± 0.113	184.41	0.058	28.86 ± 0.298	23.75	0.634	38.05 ± 0.790	22.77	0.616
VGGFace200	27.81 ± 0.29	95.70	0.023	48.94 ± 0.63	29.12	0.260	32.50 ± 0.44	66.23	0.270
VGGFace500	25.96 ± 0.32	31.90	0.031	77.76 ± 1.61	12.42	0.269	35.96 ± 0.62	43.10	0.130
VGGFace1000				108.89 ± 2.63	13.60		71.15 ± 0.93	24.07	
VGGFace2000				109.04 ± 2.44	13.79		79.51 ± 1.03	22.42	

Acknowledgements



R01: An Integrative Radiogenomic Approach to Design Genetically- Informed Image Biomarker for Characterizing COPD.



Research Sponsored: Deep Multi-Domain Learning: A Framework to Incorporate Weak Labels to the Attention Models.



Tripods+X: Learning with Expert-In-The- Loop for Multimodal Weakly Labeled Data and an Application to Massive Scale Medical Imaging.



Research Sponsored: Developing Statistical Method to Jointly Model Genotype and High Dimensional Phenotype .