# The power of two samples for Generative Adversarial Networks

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joint work with Giulia Fanti, Ashish Khetan, Zinan Lin

#### Generative models



- A generative model is a black box that takes a random vector  $Z\in\mathbb{R}^k$  and produces a sample vector  $G(Z)\in\mathbb{R}^n$
- It is a differentiable function and stochastic gradient descent is used to train *G*

<sup>1</sup>["Compressed Sensing using Generative Models", A Bora, A Jalal, E Price, AG Dimakis, 2017]

# Generative models learn representation<sup>2</sup>



<sup>2</sup>[DCGAN, Radford et al. 2015]

## Generative Adversarial Networks (GAN)



 $\min_{G} \ \max_{D} \ V(G,D)$ 

#### Mode collapse



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## Mode collapse

• "A man in a orange jacket with sunglasses and a hat ski down a hill." <sup>3</sup>



• "This guy is in black trunks and swimming underwater."



• "A tennis player in a blue polo shirt is looking down at the green court."



 $<sup>^{3}</sup>$  ["Generating interpretable images with controllable structure", by Reed et al., 2016]

# New framework: PacGAN

- lightweight overhead
- experimental results
- principled



#### Benchmark datasetes from $\mathrm{V}\mathrm{EEGAN}$ paper

Target	GAN	PacGAN2
-6 -7 3 2 8 0	Modes	high quality
	(Max 25)	samples
GAN	3.3	0.5 %
ALI	15.8	1.6 %
Unrolled GAN	23.6	16.0 %
VEEGAN	24.6	40.0 %
PacGAN2	24.6±0.9	65.8±13.4 %
PacGAN3	$24.9{\pm}0.3$	71.4±13.8 %
PacGAN4	$25.0{\pm}0.0$	76.0±7.1 %

#### Benchmark datasetes from $\operatorname{VEEGAN}$ paper



	Modes (Max 1000)	KL
DCGAN	99.0	3.40
ALI	16.0	5.40
Unrolled GAN	48.7	4.32
VEEGAN	150.0	2.95
PacDCGAN2	$1000.0{\pm}0.0$	$0.06{\pm}0.01$
PacDCGAN3	$1000.0{\pm}0.0$	$0.06{\pm}0.01$
PacDCGAN4	$1000.0{\pm}0.0$	$0.07{\pm}0.01$

#### Benchmark from Unrolled GAN (small discriminator)



	Modes (Max 1000)	KL
DCGAN	30.6±20.73	$5.99{\pm}0.42$
Unrolled GAN, 1 step	65.4±34.75	$5.91{\pm}0.14$
Unrolled GAN, 5 steps	$236.4 \pm 63.30$	4.67±0.43
Unrolled GAN, 10 steps	327.2±74.67	$4.66{\pm}0.46$
PacDCGAN2	370.8±244.34	3.33±1.02
PacDCGAN3	534.3±103.68	$2.11{\pm}0.52$
PacDCGAN4	557.7±101.37	$2.06{\pm}0.61$

#### Intuition behind packing via toy example



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#### Intuition behind packing via toy example



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#### Intuition behind packing via toy example



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#### Evolution of TV distances



Evolution of TV distances through the prism of packing



Through packing, the target-generator pairs are expanded over the strengths of the mode collapse



$$\max_{\substack{P,Q \\ P,Q}} / \min_{\substack{P,Q \\ P,Q}} \quad d_{\mathrm{TV}}(P^2,Q^2)$$
  
subject to  $\quad d_{\mathrm{TV}}(P,Q) = \tau$ 

 ${\ensuremath{\, \circ }}$  we focus on m=2 for this talk

#### Definition [mode collapse region]

We say a pair (P,Q) of a target distribution P and a generator distribution Q has  $(\varepsilon, \delta)$ -mode collapse if there exists a set S such that

 $P(S) \geq \delta \ , \qquad \text{and} \qquad Q(S) \leq \varepsilon \ .$ 

#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]



#### Definition [mode collapse region]





$$\max_{P,Q} \quad d_{\text{TV}}(P^2,Q^2)$$
  
subject to 
$$d_{\text{TV}}(P,Q) = \tau$$



$$\label{eq:transformation} \begin{split} \max_{P,Q} & d_{\mathrm{TV}}(P^2,Q^2) \\ \text{subject to} & d_{\mathrm{TV}}(P,Q) = \tau \end{split}$$

$$\mathcal{R}(P,Q) \subseteq \mathcal{R}_{outer}(\tau)$$



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$$\min_{P,Q} \qquad d_{\mathrm{TV}}(P^2,Q^2)$$
 subject to 
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$$\mathcal{R}_{inner}(\tau, \alpha) \subseteq \mathcal{R}(P, Q)$$



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 $\max_{P,Q}$  subject to

$$d_{
m TV}(P^2,Q^2)$$
  
 $d_{
m TV}(P,Q)= au$ no  $(arepsilon_0,\delta_0)$ -mode collapse







 $\begin{array}{ll} \max_{P,Q} & d_{\mathrm{TV}}(P^2,Q^2) \\ \text{subject to} & d_{\mathrm{TV}}(P,Q) = \tau \\ & \text{no} \ (\varepsilon_0,\delta_0) \text{-mode collapse} \end{array}$ 

 $\mathcal{R}(P,Q) \subseteq \mathcal{R}_{outer}(\tau,\varepsilon_0,\delta_0,\alpha)$ 



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 $\begin{array}{lll} \mathcal{R}(P,Q) & \subseteq & \mathcal{R}_{\mathrm{outer}}(\tau,\varepsilon_{0},\delta_{0},\alpha) \\ \mathcal{R}(P^{2},Q^{2}) & \subseteq & \mathcal{R}(P^{2}_{\mathrm{outer}},Q^{2}_{\mathrm{outer}}) \end{array}$ 



Blackwell's theorem  $\mathcal{R}(P,Q) \subseteq \mathcal{R}(P',Q')$  $\Rightarrow \mathcal{R}(P^2,Q^2) \subseteq \mathcal{R}(P'^2,Q'^2)$ 



 $\begin{array}{ll} \max_{P,Q} & d_{\mathrm{TV}}(P^2,Q^2) \\ \text{subject to} & d_{\mathrm{TV}}(P,Q) = \tau \\ & \mathsf{no}\;(\varepsilon_0,\delta_0)\text{-mode collapse} \end{array}$ 

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 $\min_{P,Q}$ 

 $d_{\rm TV}(P^2,Q^2)$ subject to  $d_{\mathrm{TV}}(P,Q) = \tau$  $(\varepsilon_1, \delta_1)$ -mode collapse



 $\begin{array}{ll} \min_{P,Q} & d_{\mathrm{TV}}(P^2,Q^2) \\ \text{subject to} & d_{\mathrm{TV}}(P,Q) = \tau \\ & (\varepsilon_1,\delta_1)\text{-mode collapse} \end{array}$ 



$$\begin{split} \min_{\substack{P,Q} \\ \text{subject to} } & d_{\mathrm{TV}}(P^2,Q^2) \\ & \varepsilon_{\mathrm{TV}}(P,Q) = \tau \\ & (\varepsilon_1,\delta_1)\text{-mode collapse} \end{split}$$

 $\mathcal{R}_{inner}(\tau, \alpha, \varepsilon_1, \delta_1) \subseteq \mathcal{R}(P, Q)$ 



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$$\begin{split} \min_{P,Q} & \quad d_{\mathrm{TV}}(P^2,Q^2) \\ \text{subject to} & \quad d_{\mathrm{TV}}(P,Q) = \tau \\ & \quad (\varepsilon_1,\delta_1)\text{-mode collapse} \end{split}$$

$$\begin{aligned} &\mathcal{R}_{\text{inner}}(\tau, \alpha, \varepsilon_1, \delta_1) &\subseteq & \mathcal{R}(P, Q) \\ &\mathcal{R}(P_{\text{inner}}^2, Q_{\text{inner}}^2) &\subseteq & \mathcal{R}(P^2, Q^2) \end{aligned}$$

Blackwell's theorem  $\mathcal{R}(P,Q) \subseteq \mathcal{R}(P',Q')$  $\Rightarrow \mathcal{R}(P^2,Q^2) \subseteq \mathcal{R}(P'^2,Q'^2)$ 



 $d_{\rm TV}(P^2,Q^2)$ min P,Qsubject to  $d_{TV}(P,Q) = \tau$  $(\varepsilon_1, \delta_1)$ -mode collapse  $\mathcal{R}_{inner}(\tau, \alpha, \varepsilon_1, \delta_1) \subseteq \mathcal{R}(P, Q)$  $\mathcal{R}(P_{inner}^2, Q_{inner}^2) \subseteq \mathcal{R}(P^2, Q^2)$  $\underline{d_{\mathrm{TV}}(P_{\mathrm{inner}}^2, Q_{\mathrm{inner}}^2)} \leq d_{\mathrm{TV}}(P^2, Q^2)$ simple to evaluate

Blackwell's theorem  $\mathcal{R}(P,Q) \subseteq \mathcal{R}(P',Q')$  $\Rightarrow \mathcal{R}(P^2,Q^2) \subseteq \mathcal{R}(P'^2,Q'^2)$ 

#### Achievable TV distances for distributions



with packing, the discriminator naturally penalizes  $\left(P,Q\right)$  with severe mode collapses

#### Does larger m help?



Evolution of TV distances through the prism of packing



Through the **prism** packing, the target-generator pairs are expanded over the **spectrum** of (the strengths of) mode collapse

Our paper is available at: https://arxiv.org/abs/1712.04086

- Packing is a principled solution to mode collapse
  - Lightweight overhead
  - Excellent numerical results
  - Theoretical analysis
- Exciting time for bridging the theory and practice of GAN
  - "Generalization and Equilibrium in Generative Adversarial Nets", Sanjeev Arora, Rong Ge, Yingyu Liang, Tengyu Ma, Yi Zhang
  - "Approximation and Convergence Properties of Generative Adversarial Learning", Shuang Liu, Olivier Bousquet, Kamalika Chaudhuri
  - "Compressed Sensing using Generative Models", Ashish Bora, Ajil Jalal, Eric Price, Alexandros G. Dimakis
  - "Towards Understanding the Dynamics of Generative Adversarial
  - Networks", Jerry Li, Aleksander Madry, John Peebles, Ludwig Schmidt



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