The power of two samples in generative adversarial networks

Sewoong Oh

Department of Industrial and Enterprise Systems Engineering University of Illinois at Urbana-Champaign



Generative models learn fundamental representations



Generative Adversarial Networks (GAN)



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

Challenges in training GAN

- 1. Instability: non-convergence of training loss
- 2. Evaluation: likelihood is not available
- 3. Mode collapse: loss of diversity

"Mode collapse" is a main challenge



"Mode collapse" is a main challenge



Target samples

Generated samples



"Mode collapse" is a main challenge

• "A man in a orange jacket with sunglasses and a hat ski down a hill."



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



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



^{[&}quot;Generating interpretable images with controllable structure", by Reed et al., 2016]

Lack of diversity is easier to detect if the discriminator sees multiple sample jointly

- "Improved Techniques for Training GANs", Salimans, Goodfellow, Zaremba, Cheung, Radford, Chen, 2016
- "Progressive Growing of GANs for Improved Quality, Stability, and Variation", Karras, Aila, Laine, Lehtinen, 2017
- "Distributional Adversarial Networks", Li, Alvarez-Melis, Xu, Jegelka, Sra, 2017

New framework: PacGAN

- lightweight overhead
- experimental results
- principled



Benchmark tests



	Modes
	(Max 25)
GAN	17.3
PacGAN2	23.8
PacGAN3	24.6
PacGAN4	24.8

Benchmark datasets from VEEGAN paper



	Modes (Max 1000)
DCGAN	99.0
ALI	16.0
Unrolled GAN	48.7
VEEGAN	150.0
PacDCGAN2	1000.0
PacDCGAN3	1000.0
PacDCGAN4	1000.0

Intuition behind packing via toy example



Intuition behind packing via toy example



11/21

Intuition behind packing via toy example



11/21

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



- we focus on m=2 for this talk
- this is easy, but we have a new proof technique
- nothing to do with mode collapse, but we use it as proof technique

Definition [mode collapse region]

We say a pair (P,Q) of a target distribution P and a generator distribution Q has (ε, δ) -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
$$d_{\text{TV}}(P,Q) = \tau$$



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

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



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

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







PacGAN naturally penalizes mode collapse



PacGAN naturally penalizes mode collapse



PacGAN naturally penalizes mode collapse



Size of the discriminator



Mini-batch discrimination requires +38,748,557, PacGAN2 requires +54

0-1 loss (Total Variation) vs. cross entropy loss (Jensen-Shannon Divergence)





Jensen-Shannon is better measure for detecting mode collapse

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

All codes for the experiments at: https://github.com/fjxmlzn/PacGAN



Zinan Lin (CMU) Ashish Khetan (UIUC) Giulia Fanti (CMU)