DL-SEMINAR SEASON 5 AI LAB

조충현

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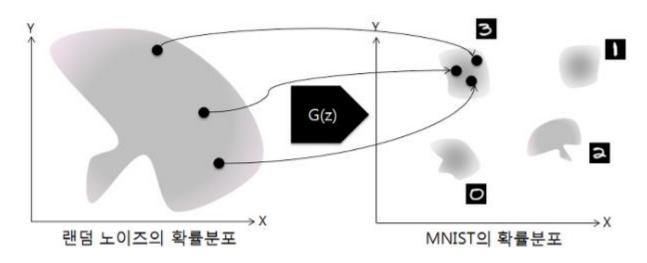
Generative model

- VAE (variational auto-encoder)
 - 단점: 이미지 생성시 blurry한 샘플을 생성

- GAN (generative adversarial network)
 - 단점: encode가 존재 하지 않음(주어진 데이터로부터 latent variable z를 뽑아내지 못 함), 학습이 어렵고, Model collapse 문제가 발생

Mode collapsing



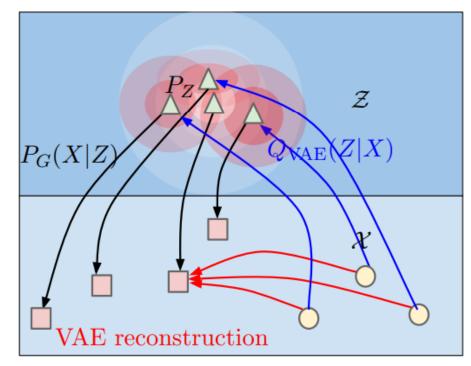


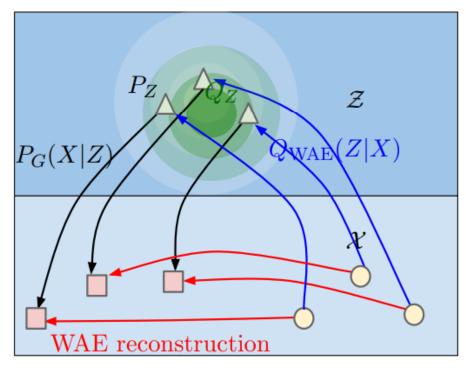
Mode: 최빈값

같은 숫자만 계속해서 생성되는 현상의 원 인이 mode collapsing

- True data distribution : P_X
- Latent variable model : P_G
- Prior distribution : P_Z
- Generative model of X given $Z:P_G(X\mid Z)$

(a) VAE (b) WAE





Optimal Transport

$$\int \left[\int c(x,y)p(x,y)dy \right] dx.$$

$$W_c(P_X, P_G) := \inf_{\Gamma \in \mathcal{P}(X \sim P_X, Y \sim P_G)} \mathbb{E}_{(X,Y) \sim \Gamma}[c(X,Y)]$$

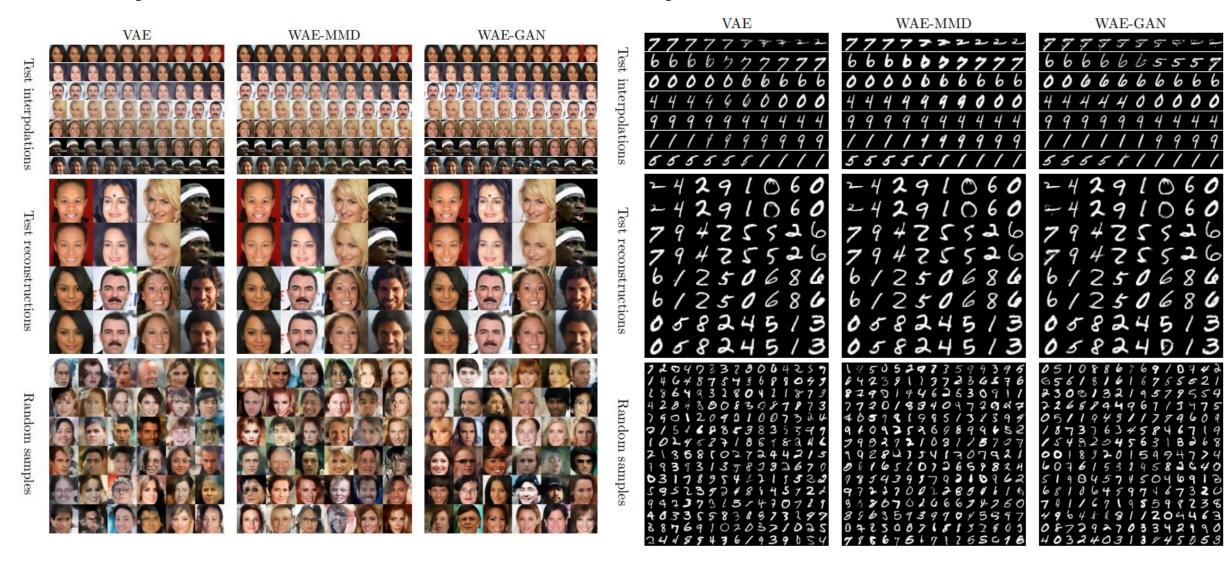
$$\inf_{\Gamma \in \mathcal{P}(X \sim P_X, Y \sim P_G)} \mathbb{E}_{(X,Y) \sim \Gamma} \left[c(X,Y) \right] = \inf_{Q \colon Q_Z = P_Z} \mathbb{E}_{P_X} \mathbb{E}_{Q(Z|X)} \left[c(X,G(Z)) \right],$$

최종 WAE:

$$D_{\text{WAE}}(P_X, P_G) := \inf_{Q(Z|X) \in \mathcal{Q}} \mathbb{E}_{P_X} \mathbb{E}_{Q(Z|X)} \left[c(X, G(Z)) \right] + \lambda \cdot \mathcal{D}_Z(Q_Z, P_Z),$$

- GAN based \mathcal{D}_Z : $D_{JS}(Q_Z, P_Z)$ 와 adversarial training을 활용. 특히 discriminator가 \mathcal{Z} space 상에서 P_Z 로부터의 true sample 과 Q_Z 로부터의 fake sample을 구분하도록 만듬.
- MMD based \mathcal{D}_Z : Positive-definite reproducing kernel $k: \mathcal{Z} \times \mathcal{Z} \to \mathcal{R}$ 에 대해 maximum mean discrepancy (MMD)는 $\mathrm{MMD}_k(P_Z,Q_Z) = \|\int_{\mathcal{Z}} k(z,\cdot) dP_Z(z) \int_{\mathcal{Z}} k(z,\cdot) dQ_Z(z)\|_{\mathcal{H}_k}$

Experiments and Comparison



Experiments and Comparison

Algorithm	FID	Sharpness
VAE	63	3×10^{-3}
WAE-MMD	55	6×10^{-3}
WAE-GAN	42	6×10^{-3}
True data	2	2×10^{-2}