无监督学习　　生成模型
- GAN
- VAE
- RBM
- ……

· VAE

$x \longrightarrow$ encoder $\begin{cases} \mu \\ \sigma \end{cases}$

style?

$z \sim N(0,1) \longrightarrow \left[\mu \cdot (z) + \sigma\right] \longrightarrow$ decoder

GAN

$z \longrightarrow G \longrightarrow G(z) \longrightarrow D(x)$ real / fake

latent space

x sample $\longrightarrow D(x)$

Problem

- 不收敛　Model collapse
- 评价问题　inception scale
- latent space 解耦.　property of latent space are poorly understood
- feature injection $\longrightarrow$ different scale

Model collapse:

$$G_{x\sim p_g}[-\log(D^*_G(x))] = KL(p_g \| p_{data}) - 2JS(p_{data} \| p_g) + E_{x\sim p_{data}}[\log D^*_G(x)] + 2\log 2$$

$p_{data}(x) \to 0$, $p_g(x) \to 1$ $\boxed{x\text{集中}}$ $KL(p_g \| p_{data}) \to +\infty$ incorrectre

$p_{data}(x) \to 1$, $p_g(x) \to 0$ $\boxed{x\text{不正确}}$ $KL(p_g \| p_{data}) \to 0$ not diverse enough

Disentangled representation GAN [68]

DR-GAN

BiGAN

$z \to G \to G(z)$ $G(z), z$

$E(x) \leftarrow E \leftarrow x$ $E(x), x$

$\boxed{\text{OR}} \to D$ Real / Fake

AGE

Evaluation Metric

transfer learning

Visulizing and Understanding Convolutional Networks

改进

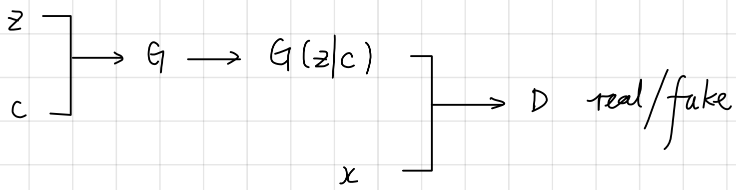
网络结构

DCGAN $\longrightarrow$ deconvolution

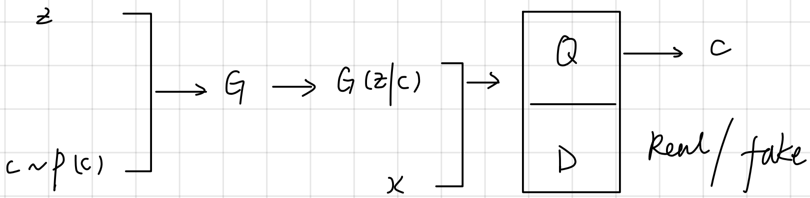
Feature editting

Latent space

· CGAN



· Info GAN $\longrightarrow$ 一定可解释性.



互信息. $I(c; G(z|c)) = H(c) - H(c \mid G(c|x))$

C与 $G(z|c)$ 的相关性

调整 c $\longrightarrow$ 三维人脸转动

$$H(c) = -\sum_{x \in C} P(x) \log P(x) = -\mathbb{E}_{x \sim C} \log C(x)$$

$$H(c \mid G(z|c)) = -\sum_{x \in c|G(z|c)} P(x) \cdot \log P(x) = -\mathbb{E}_{x \sim c|G(z|c)} \log c|G(z|c)(x)$$

· 分布式学习?

正则方法 (Style 诞生)

Batch Normalization

layer n

$$\ldots \longrightarrow \begin{array}{l} \mu_B = \frac{1}{m}\sum_{i=1}^{m} u_i \\ \sigma_B^2 = \frac{1}{m}\sum (u_i - \mu_B)^2 \end{array} \longrightarrow \hat{u}_i = \frac{u_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$h_i = \gamma \hat{u}_i + \beta$$

relu

可学习参数

Batch Normalization

$$BN(x) = \gamma\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \beta$$

$x \in \mathbb{R}^{N \times C \times H \times W}$

independent for each channel

$$\mu_c(x) = \frac{1}{NHW}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{nchw}$$

$$\sigma_c(x) = \sqrt{\frac{1}{NHW}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{w=1}^{W}\left(x_{nchw} - \mu_c(x)\right)^2 + \epsilon}$$

Instance Normalization

$$IN(x) = \gamma\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \beta$$

$x \in \mathbb{R}^{N \times C \times H \times W}$

$$IN_{nc}(x) = \gamma\left(\frac{x - \mu_{nc}(x)}{\sigma(x)}\right) + \beta$$

$$\mu_{nc}(x) = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{nchw}$$

$$\sigma_{nc}(x) = \sqrt{\frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W}\left(x_{nchw} - \mu_{nc}(x)\right)^2 + \epsilon}$$

independent for each channel, Sample

Conditional Istance Normalization

$$IN(x) = \gamma\left(\frac{x-\mu(x)}{\sigma(x)}\right)+\beta$$

$$\mu_{nc}(x) = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{nchw}$$

$x \in \mathbb{R}^{N\times C\times H\times W}$

$$\sigma_{nc}(x) = \sqrt{\frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W}(x_{nchw}-\mu_{nc}(x))^2+\epsilon}$$

$$IN_{nc}(x) = \gamma^{s}\left(\frac{x-\mu_{nc}(x)}{\sigma(x)}\right)+\beta^{s}$$

independent for each channel, sample

determined by given style produced by style transfer layer.

Adaptive Istance Normalization

$$AdaIN(x) = \gamma\left(\frac{x-\mu(x)}{\sigma(x)}\right)+\beta$$

$$\mu_{nc}(x) = \frac{1}{HW}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{nchw}$$

$x \in \mathbb{R}^{N\times C\times H\times W}$

$$\sigma_{nc}(x) = \sqrt{\frac{1}{HW}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{w=1}^{W}(x_{nchw}-\mu_{c}(x))^2+\epsilon}$$

$$AdaIN_{nc}(x) = \sigma(y)\left(\frac{x-\mu_{nc}(x)}{\sigma(x)}\right)+\mu(y)$$

independent for each channel, Sample

learnable prarameter from style input.

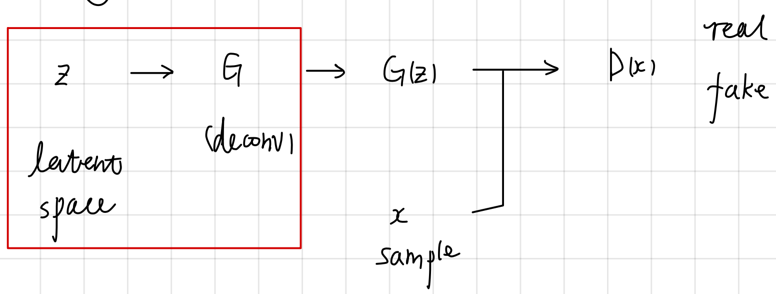
c content $\longrightarrow$ f Encoder vgg19 pretrained $\rightarrow f(c), f(s) \xrightarrow{AdaIN} t = AdaIN(f(c), f(s)) \rightarrow$ decoder untrained.

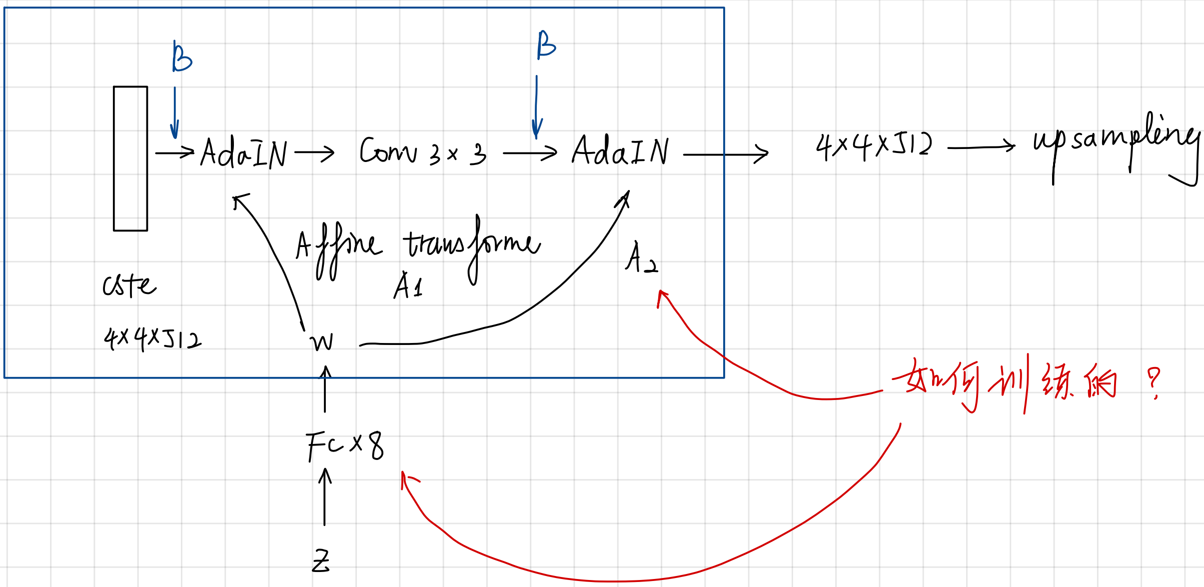
s style $\longrightarrow$

data size?

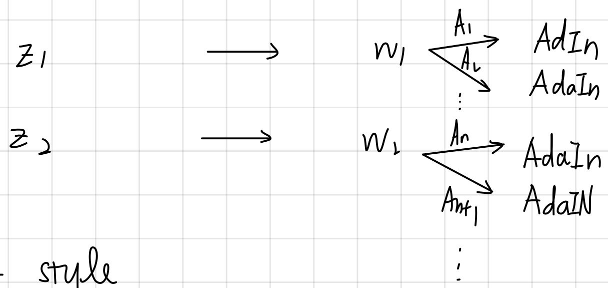
Style GAN

changed both architecture and Batch Normalization





Style Mixing : switching latent code z at a radomly chosen point



z —— style

detrangle ?

$\boxed{\text{优化算法}}$ Simultaneous gradient ascent

GAN - Reinforcement learning

用户修改自动对照片进行编译　　feature editting.

iGAN

Pix 2 Pix　成对数据

Cycle GAN

生成式模仿学习　示教数据学习专家策略的问题

IRL　　生成式模仿学习 GAIL

应用方向
- 隐变量 ⟶ 目标空间映射　$\boxed{\text{DDPG}}$
- 强化学习方向应用