

Hung-yi Lee Generative Adversaria

Generator: a neural network

Gan discriminator predict

假设数据集内部元素呈现线性分布, 于是可以遍历的方式拿到所有可能的数据集, 这些数据及在discriminator中分数最高的即为预测值, 这些数据集中, 属于training的应该让discriminator给出高分, 不属于training的discriminator应该给出低分, 借此完成discriminator的独立training

Gan Feature Extraction

infoGan

InfoGan

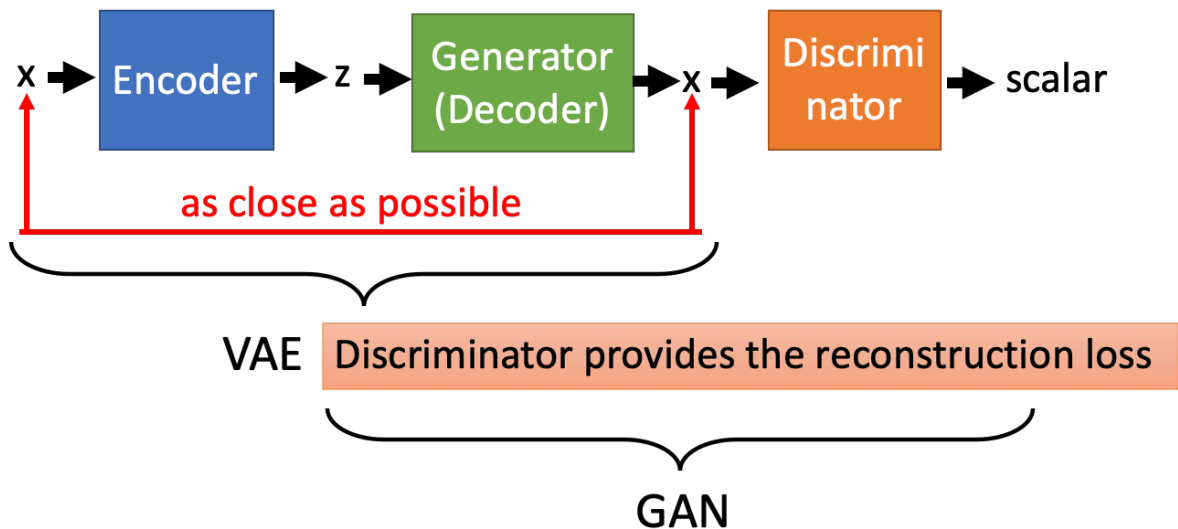
假设我们打算生成像MNIST那样的手写数字图像, 每个手写数字可以分解成多个维度特征: 代表的数字、倾斜度、粗细度等等, 在标准GAN的框架下, 我们无法在上述维度上具体指定Generator生成什么样的手写数字。

为了解决这一问题, 文章对GAN的目标函数进行了一些小小的改进, 成功让网络学习到了可解释的特征表示(即论文题目中的interpretable representation)。

[infoGan理解](#)

VAE-GAN

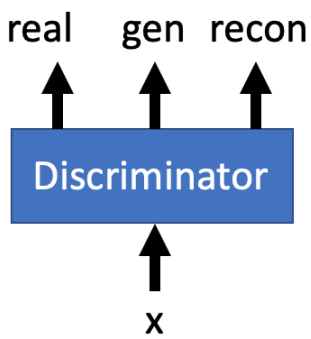
- Minimize reconstruction error
- z close to normal
- Minimize reconstruction error
- Cheat discriminator
- Discriminate real, generated and reconstructed images



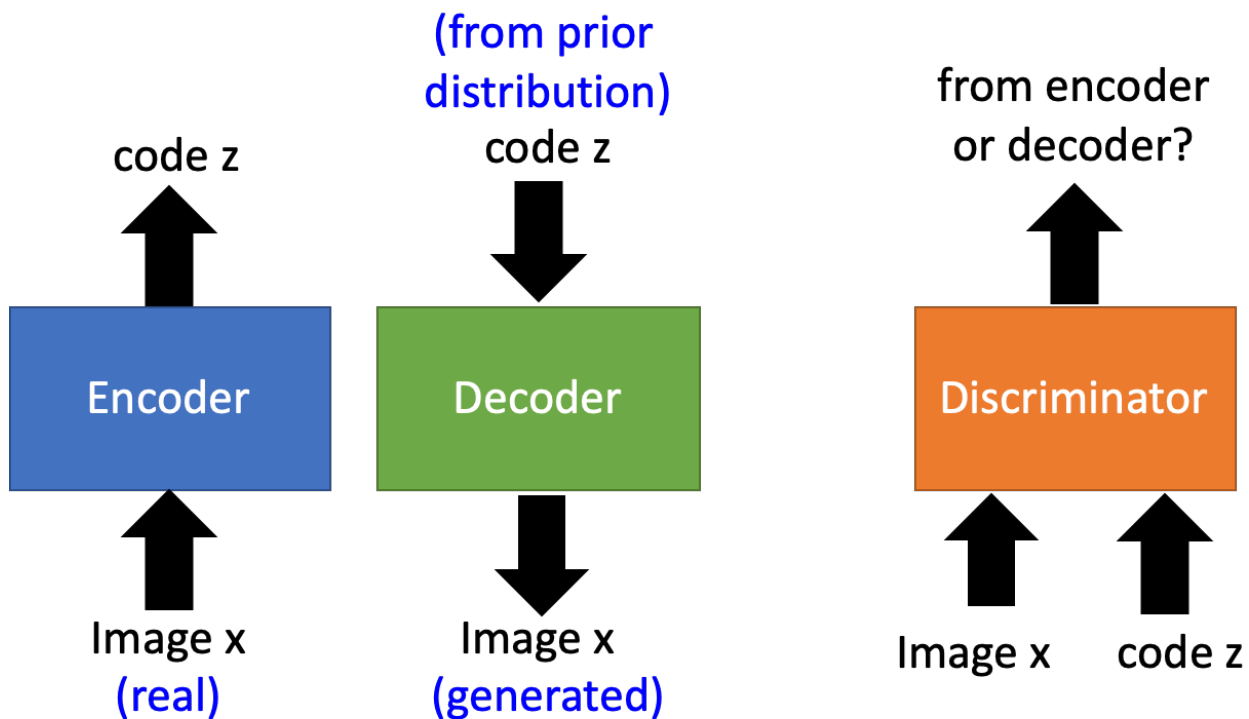
Algorithm

- Initialize En, De, Dis
- In each iteration:
 - Sample M images x^1, x^2, \dots, x^M from database
 - Generate M codes $\tilde{z}^1, \tilde{z}^2, \dots, \tilde{z}^M$ from encoder
 - $\tilde{z}^i = En(x^i)$
 - Generate M images $\tilde{x}^1, \tilde{x}^2, \dots, \tilde{x}^M$ from decoder
 - $\tilde{x}^i = De(\tilde{z}^i)$
 - Sample M codes z^1, z^2, \dots, z^M from prior $P(z)$
 - Generate M images $\hat{x}^1, \hat{x}^2, \dots, \hat{x}^M$ from decoder
 - $\hat{x}^i = De(z^i)$
 - Update En to decrease $\|\tilde{x}^i - x^i\|$, decrease $KL(P(\tilde{z}^i | x^i) || P(z))$
 - Update De to decrease $\|\tilde{x}^i - x^i\|$, increase $Dis(\tilde{x}^i)$ and $Dis(\hat{x}^i)$
 - Update Dis to increase $Dis(x^i)$, decrease $Dis(\tilde{x}^i)$ and $Dis(\hat{x}^i)$

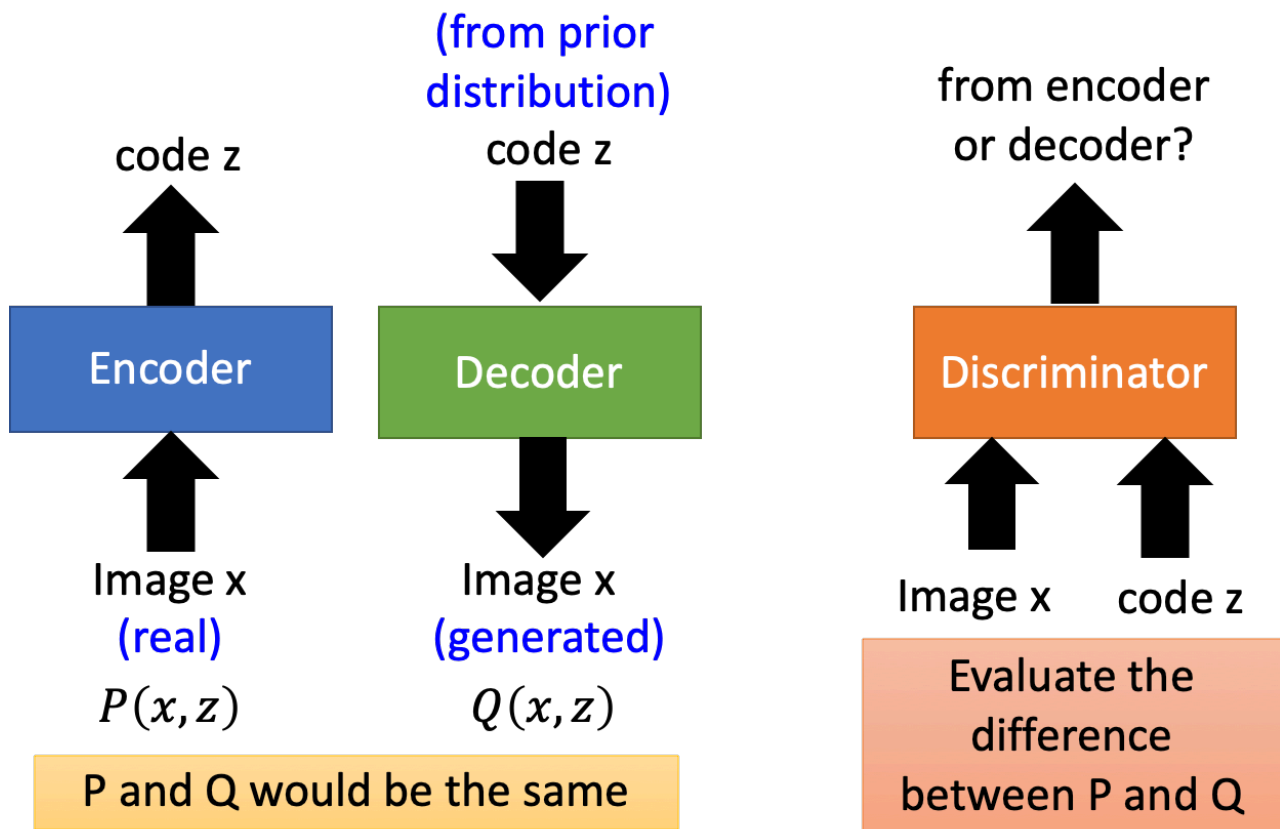
Another kind of discriminator:



BiGan



- Initialize encoder En , decoder De , discriminator Dis
- In each iteration:
 - Sample M images x^1, x^2, \dots, x^M from database
 - Generate M codes $\tilde{z}^1, \tilde{z}^2, \dots, \tilde{z}^M$ from encoder
 - $\tilde{z}^i = En(x^i)$
 - Sample M codes z^1, z^2, \dots, z^M from prior $P(z)$
 - Generate M codes $\tilde{x}^1, \tilde{x}^2, \dots, \tilde{x}^M$ from decoder
 - $\tilde{x}^i = De(z^i)$
 - Update Dis to increase $Dis(x^i, \tilde{z}^i)$, decrease $Dis(\tilde{x}^i, z^i)$
 - Update En and De to decrease $Dis(x^i, \tilde{z}^i)$, increase $Dis(\tilde{x}^i, z^i)$



Optimal encoder and decoder:

$$\begin{aligned} \text{En}(x') = z' &\Rightarrow \text{De}(z') = x' && \text{For all } x' \\ \text{De}(z'') = x'' &\Rightarrow \text{En}(x'') = z'' && \text{For all } z'' \end{aligned}$$

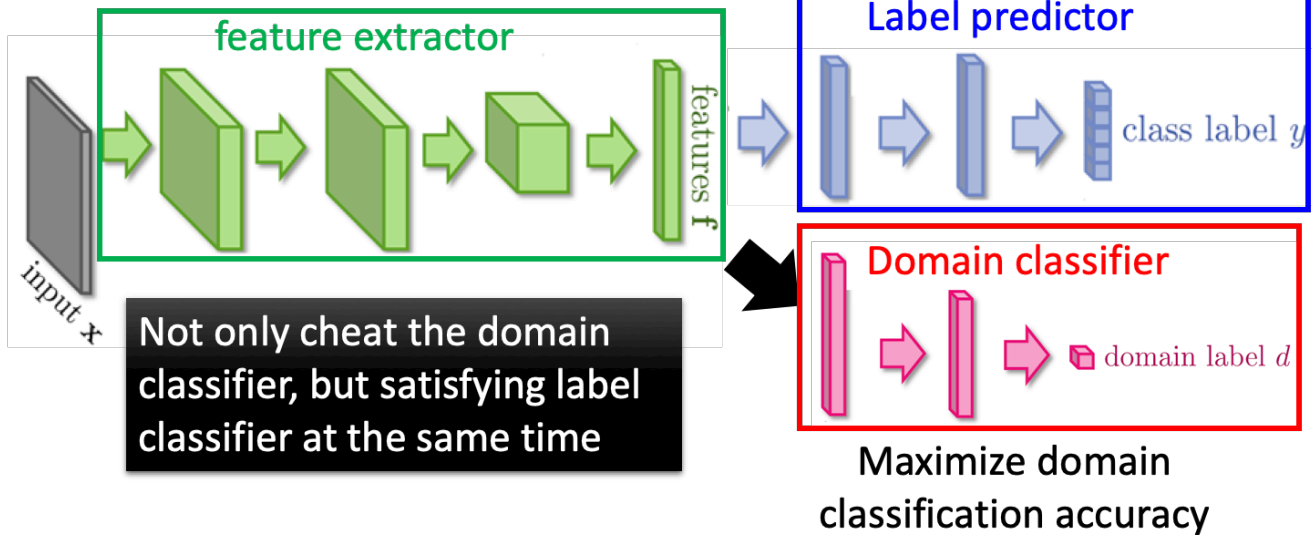
让encoder与decoder越相似越好

Bigan得到的auto encoder与一半的auto-encoder特性不一样

Triple Gan

Domain-adversarial training

Maximize label classification accuracy +
minimize domain classification accuracy



This is a big network, but different parts have different goals.