

# VAE

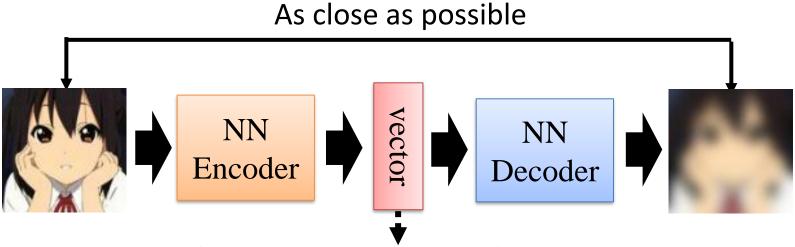
赵洲 浙江大学计算机学院

# VAE模型家族

AE

■ VAE

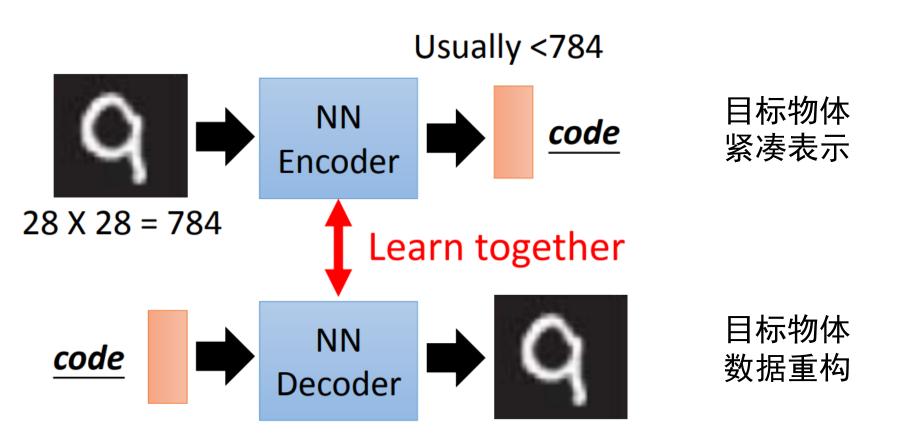
#### Auto-encoder



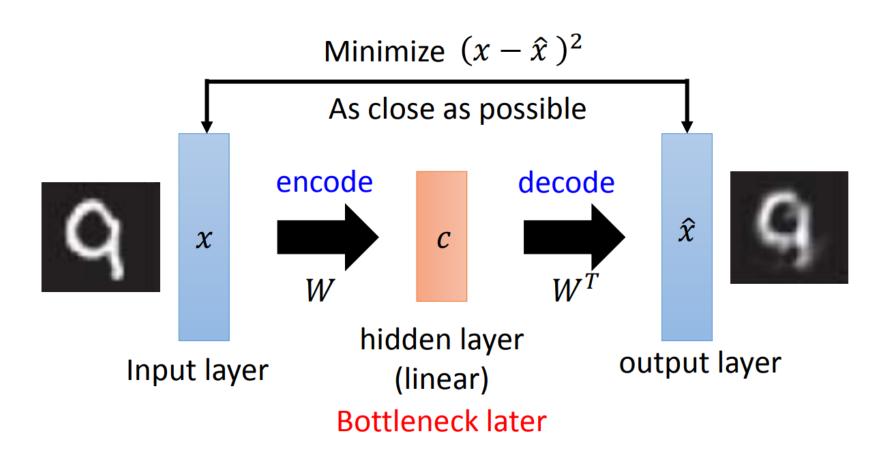
Embedding, Latent Representation, Latent Code

- More than minimizing reconstruction error
- More interpretable embedding

#### Auto-encoder (MINIST)

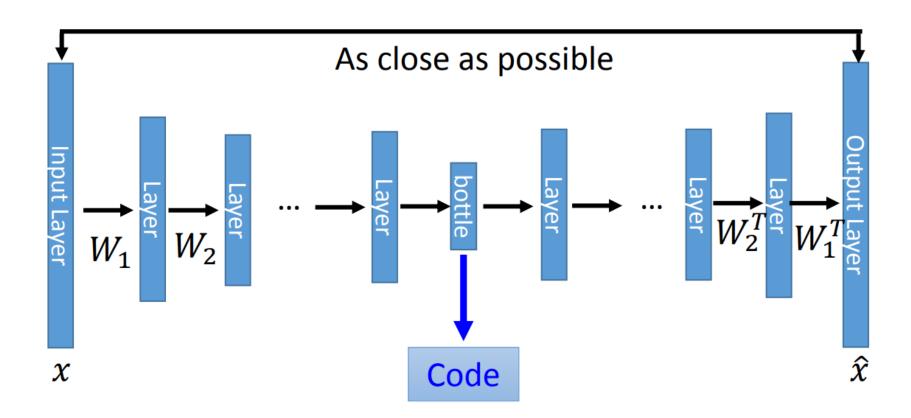


#### 与PCA等降维方法联系

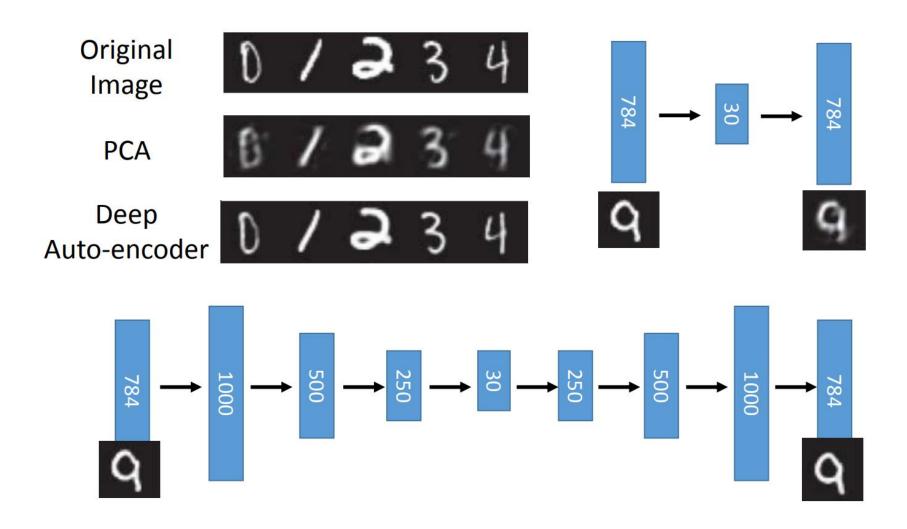


#### 线性层的输出是目标物体的编码

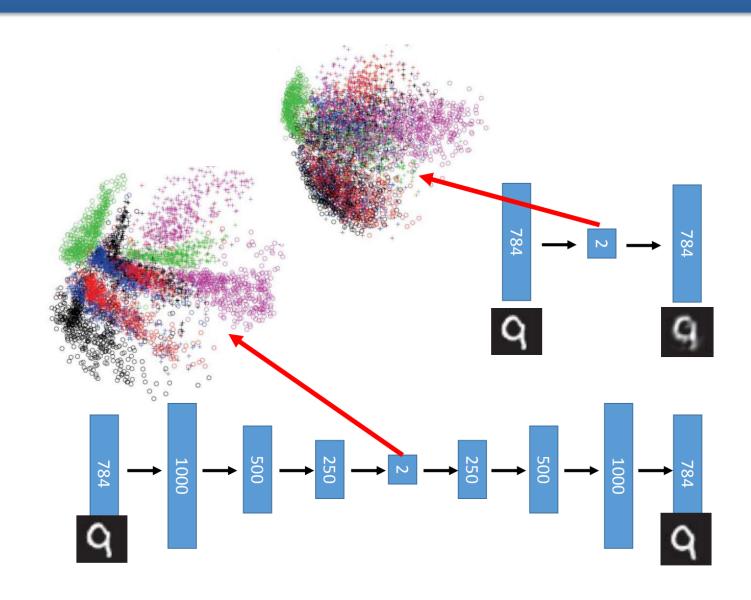
## 深度Auto-encoder



## 与PCA等降维方法对比

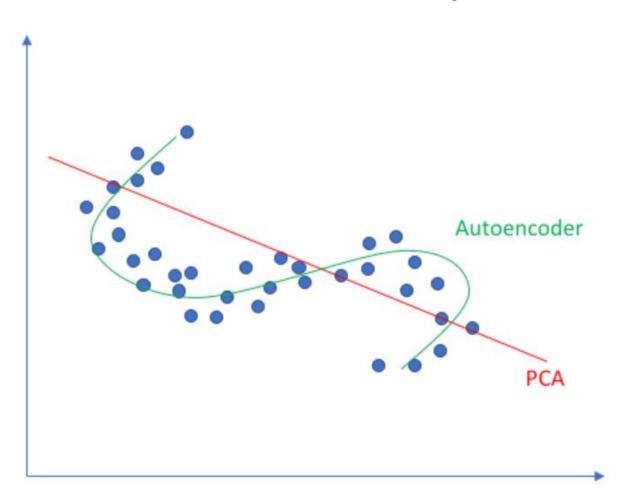


# 编码可视化

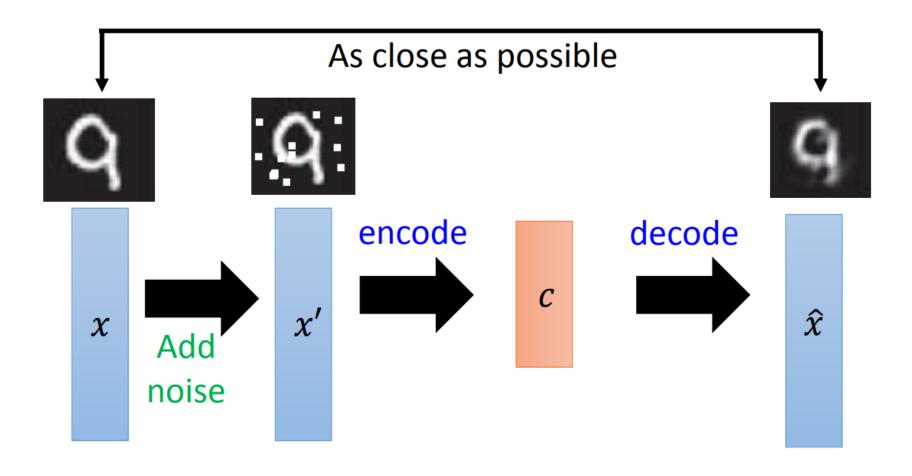


# PCA的非线性泛化

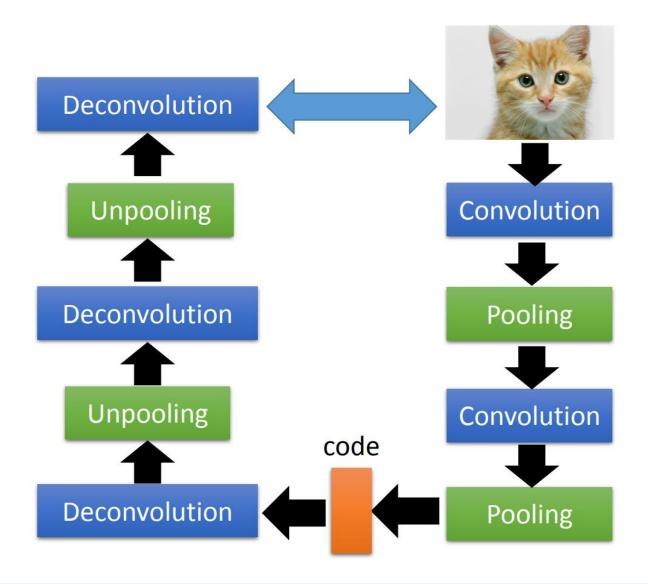
#### Linear vs nonlinear dimensionality reduction



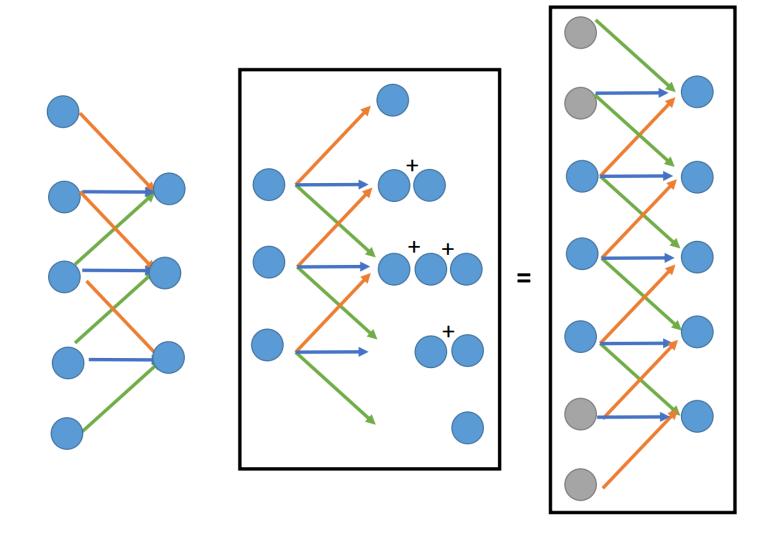
# 去噪Auto-encoder



## 基于CNN的Auto-encoder

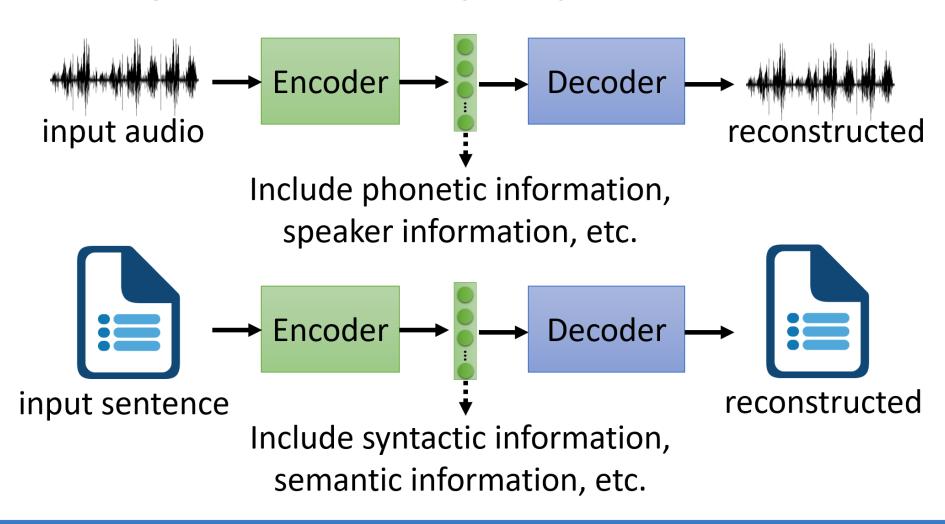


### Deconvolution

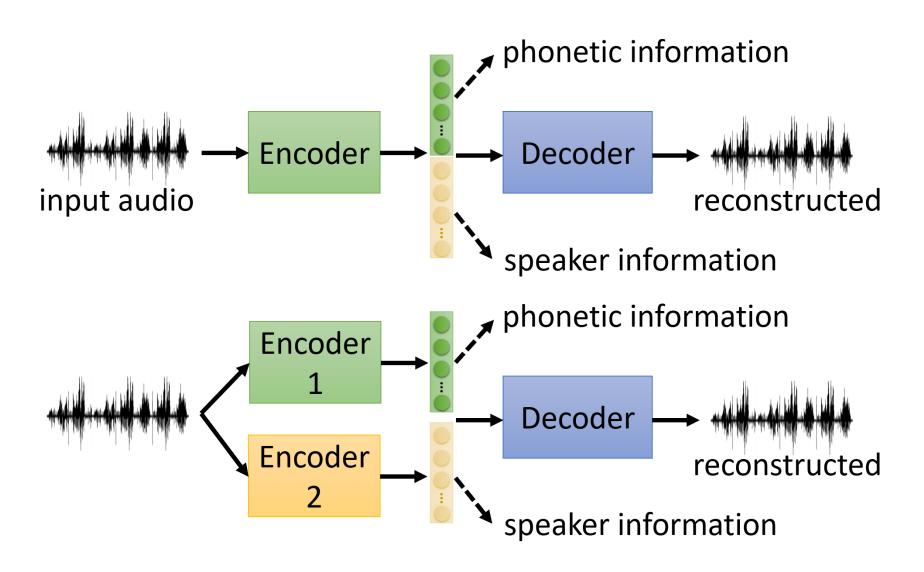


#### Auto-encoder (特征解耦)

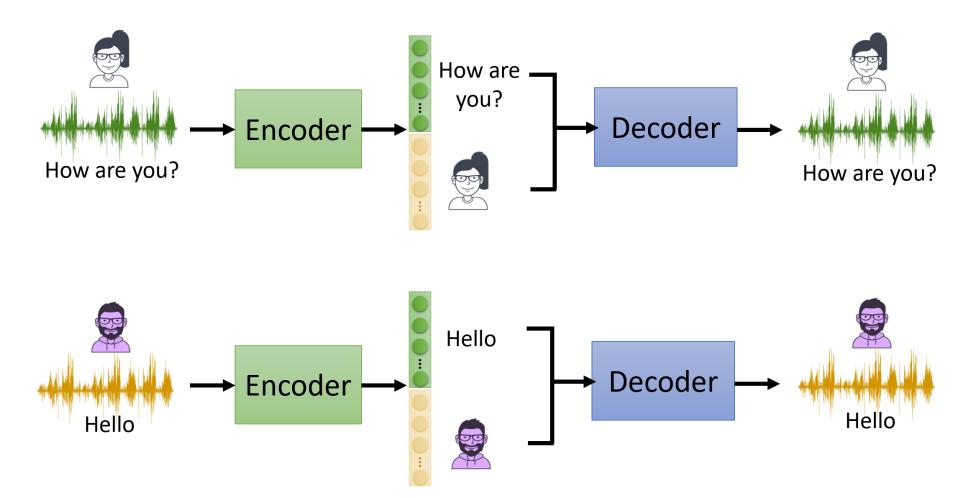
An object contains multiple aspect information



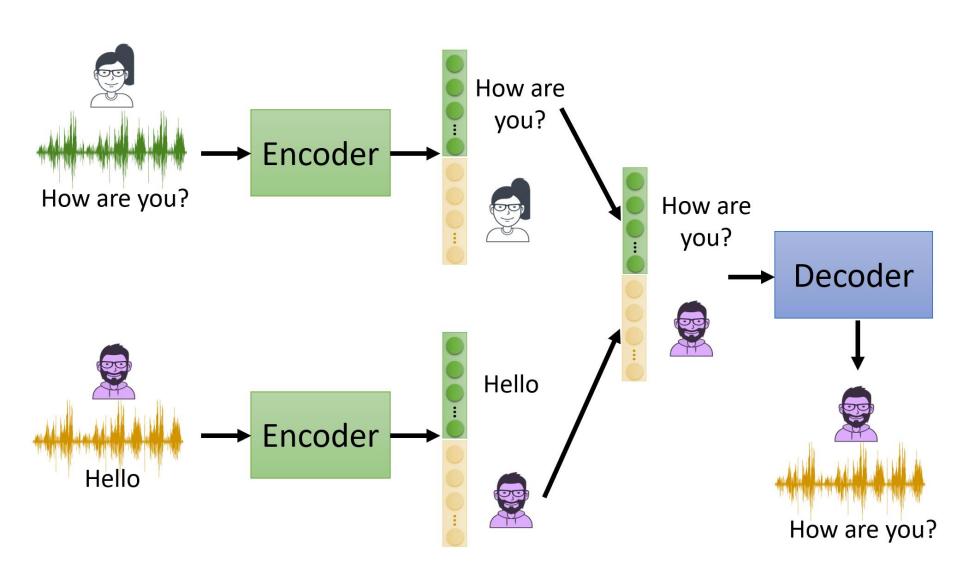
### 特征解耦



# 语音转换



# 语音转换



### 例子

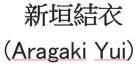


Do you want to study a PhD?

Go away!



Student





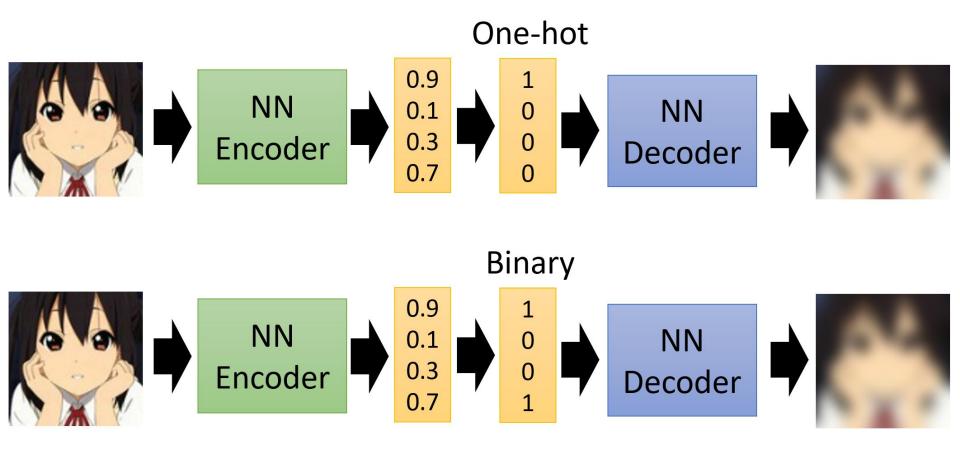
Do you want to study a PhD?



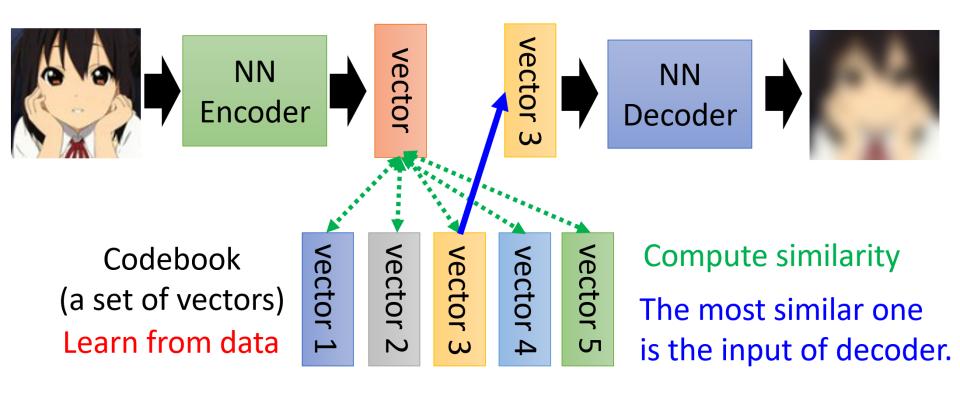


Student

# 离散表示(VQ-VAE)



## 离散表示(VQ-VAE)



#### AE的问题

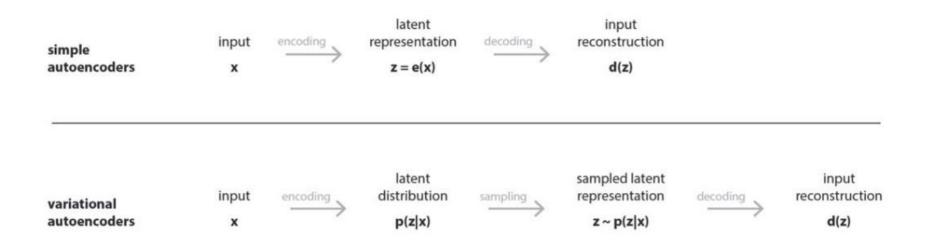
■ AE通过编码器z = g(X),将每个图片编码成向量z;它的解码器 f(z)利用编码向量z来重构原始图片。

■ 当AE作为合成模型,针对随机生成的编码向量z,f(z)只会生成一些没有意义的噪声。

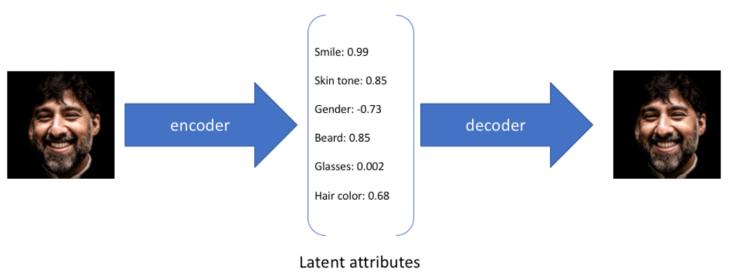
■ 原因在与AE没有对z的分布p(z)进行建模,所以不确定哪些z能够生成有用的图片(训练f(z)数据有限,f只能对极有限的z响应,而编码向量是一个太大的空间)。

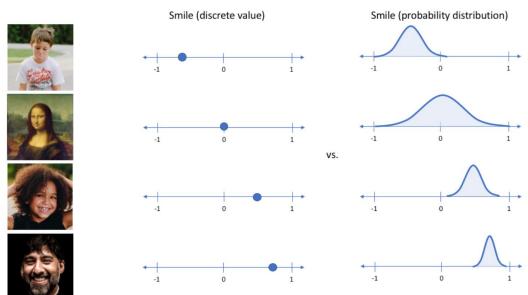
#### 从AE到VAE

■ 在AE的基础上,显性对z的分布p(z)进行建模,使得自编码器成为一个合格的生成模型(VAE)。

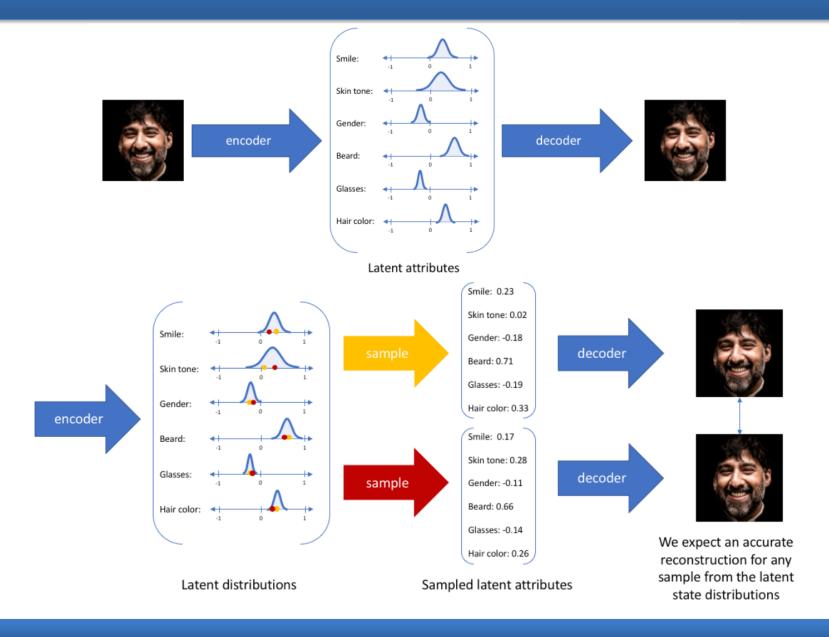


#### 例子解释

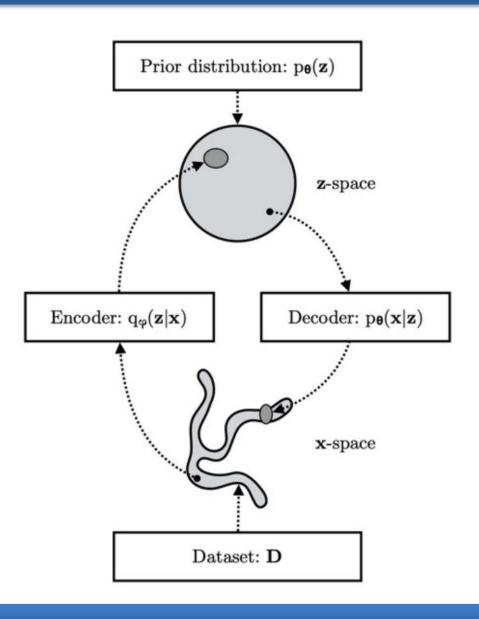




## 例子解释



# VAE的编码和解码过程



#### 优化目标

$$\mathcal{L}_{VAE} = -\lambda D(q_{\phi}(z) \| p(z)) + \mathbb{E}_{p_{data}(x)} \mathbb{E}_{q_{\phi}(z|x)} \left[ \log p_{ heta}(x|z) 
ight]$$

