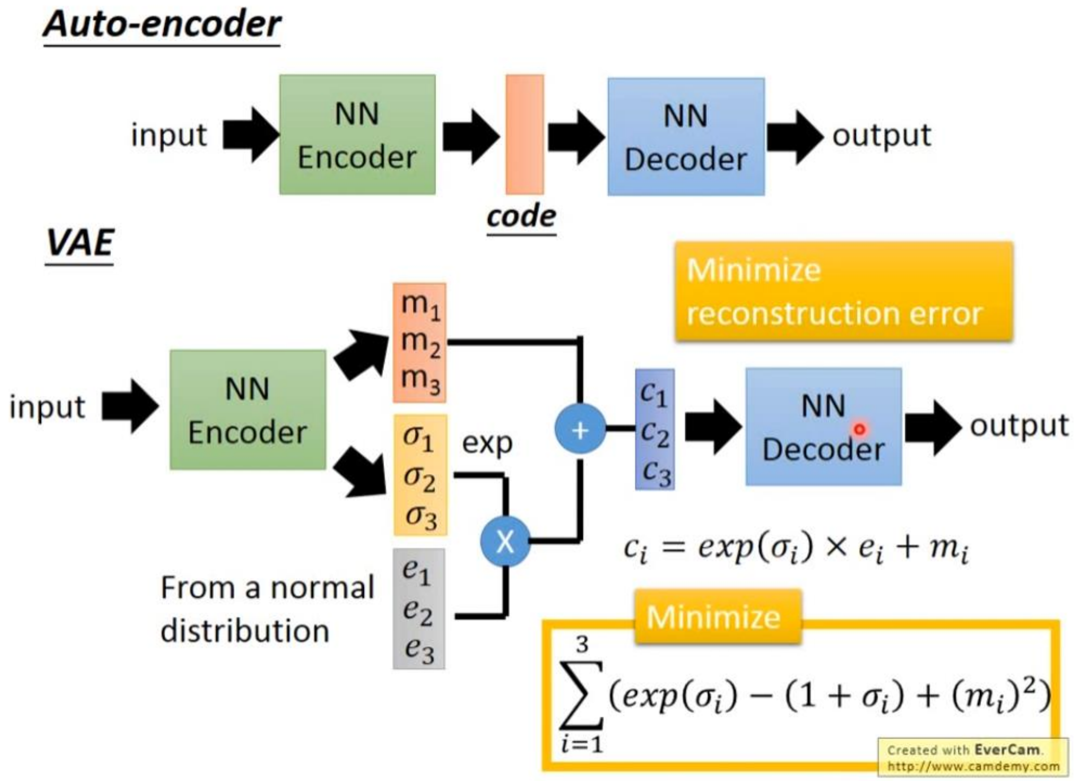
1. Make a brief introduction about variational autoencoder (VAE). List one advantage comparing with vanilla autoencoder and one problem of VAE.

與一般的 Autoencoder 不同的地方是，我們將隱含向量增加一點限制，迫使其生成的隱含向量能夠粗略的遵循一個標準正態分布，之後我們只需要給它一個標準正態分布的隨機隱含向量即可生成圖片(一般的 Autoencoder 需透過 Encoder 才能得到隱含向量)



優: 可以通過編碼解碼的步驟，直接比較重建圖片和原始圖片的差異(理論上可以控制圖片的生成)

缺: VAE 趨向於產生模糊的圖片

Ref:

https://yuanxiaosc.github.io/2018/08/26/%E5%8F%98%E5%88%86%E8%87%AA%E7%BC%96%E7%A0%81%E5%99%A8/

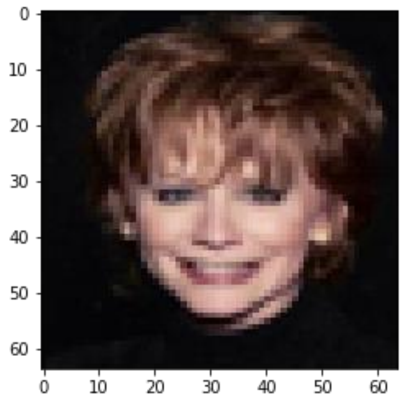
https://www.youtube.com/watch?v=8zomhgKrsmQ

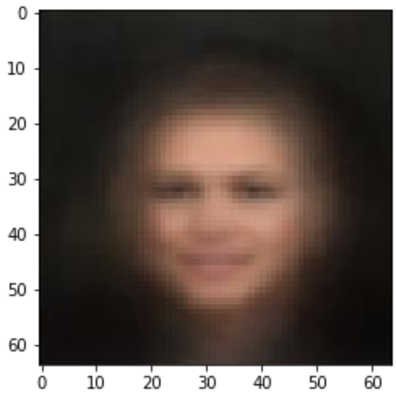
https://www.796t.com/content/1534172182.html

2. Train a fully connected autoencoder and adjust at least two different element of the latent representation. Show your model architecture, plot out the original image, the reconstructed images for each adjustment and describe the differences.

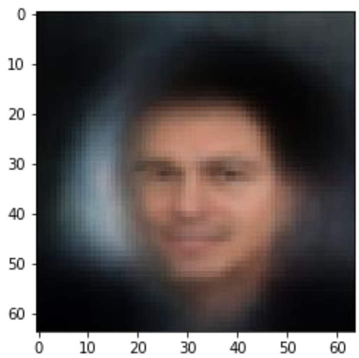
In [8]:
```
model
```

Out[8]:
```
fcn_autoencoder(
  (encoder): Sequential(
    (0): Linear(in_features=12288, out_features=12, bias=True)
    (1): ReLU()
  )
  (decoder): Sequential(
    (0): Linear(in_features=12, out_features=12288, bias=True)
    (1): Tanh()
  )
)
```

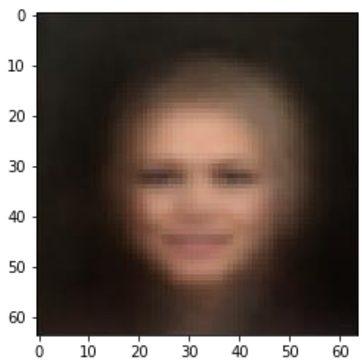





```
if model_type in ['fcn']:
    img = img.reshape(img.shape[0], -1)
    x = model.encoder(img)
    x[0][0] = x[0][0]*3
    output = model.decoder(x)
```

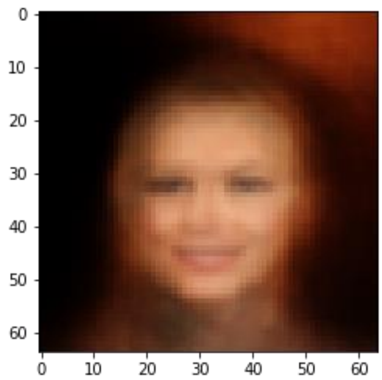



```
x[0][0] = x[0][0]/3
```



更改第 0 維的值會改變性別，大的值偏男性，小的值偏女性

x[0][2] = x[0][2]*3



x[0][2] = x[0][2]/3

更改第 2 維的值會改變顏色，大的值偏紅色，小的值偏藍色

但除了更改上述的特徵，對嘴巴的開合與背景膚色都會造成影響，感覺無法將特徵分離開來