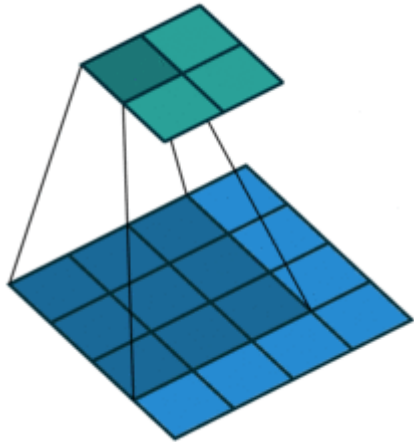


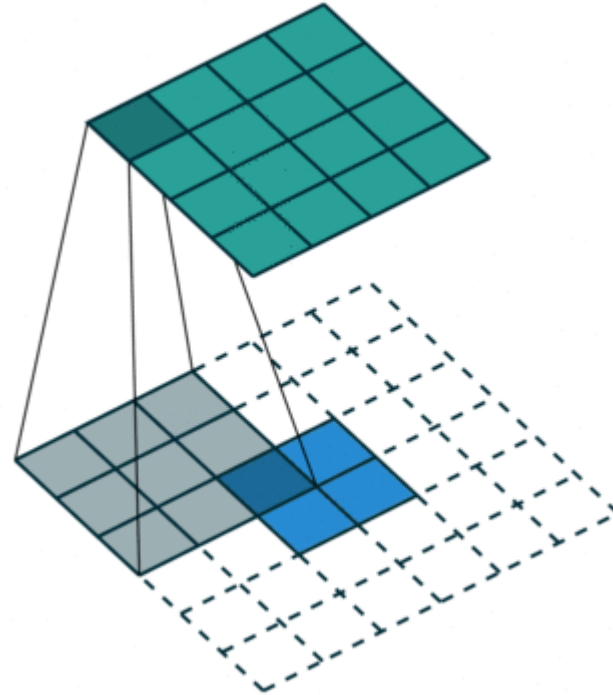
# InfoGAN

助教：來俊聖

# Conv Layer v.s. ConvTranspose Layer



Conv Layer

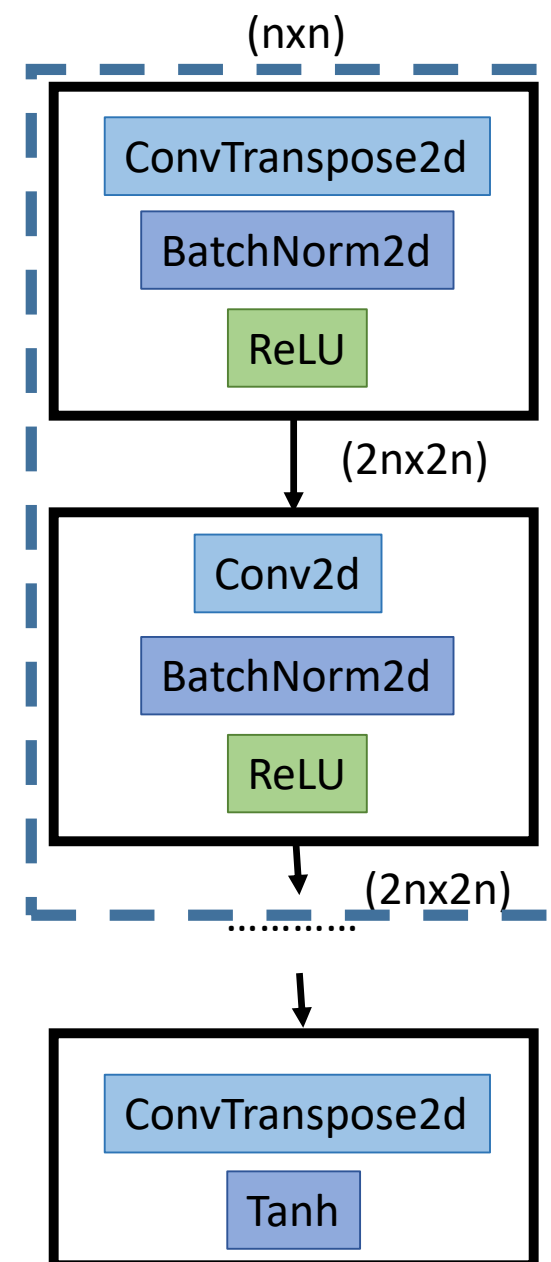
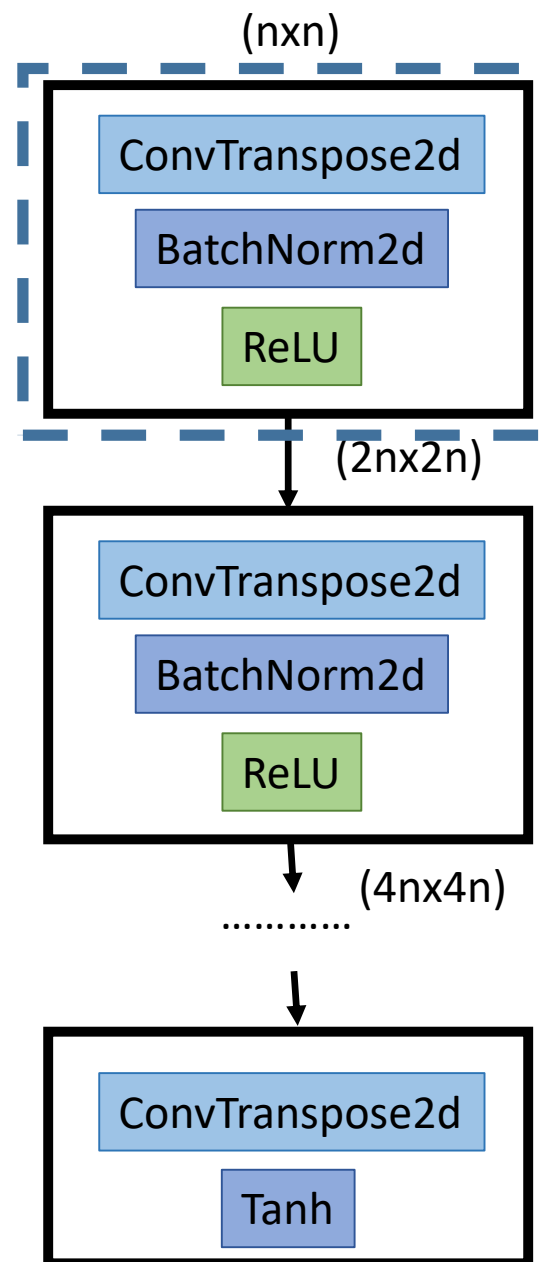
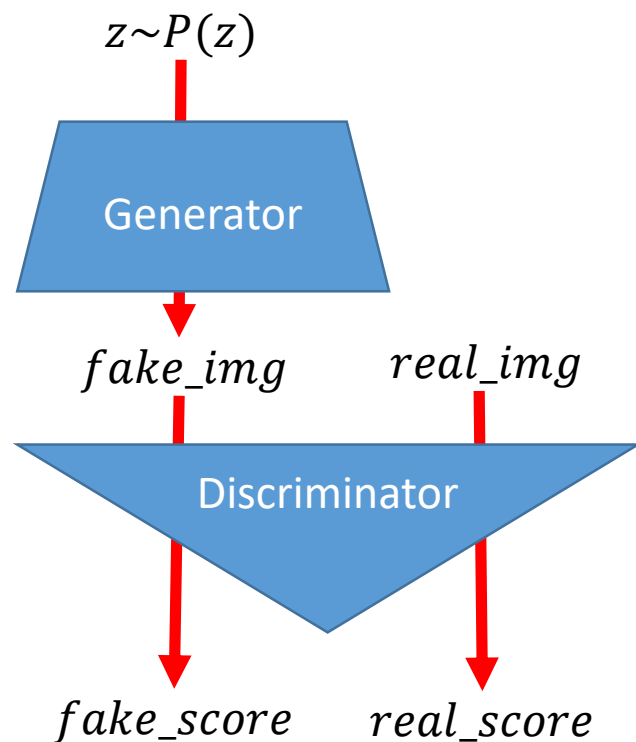


ConvTranspose Layer

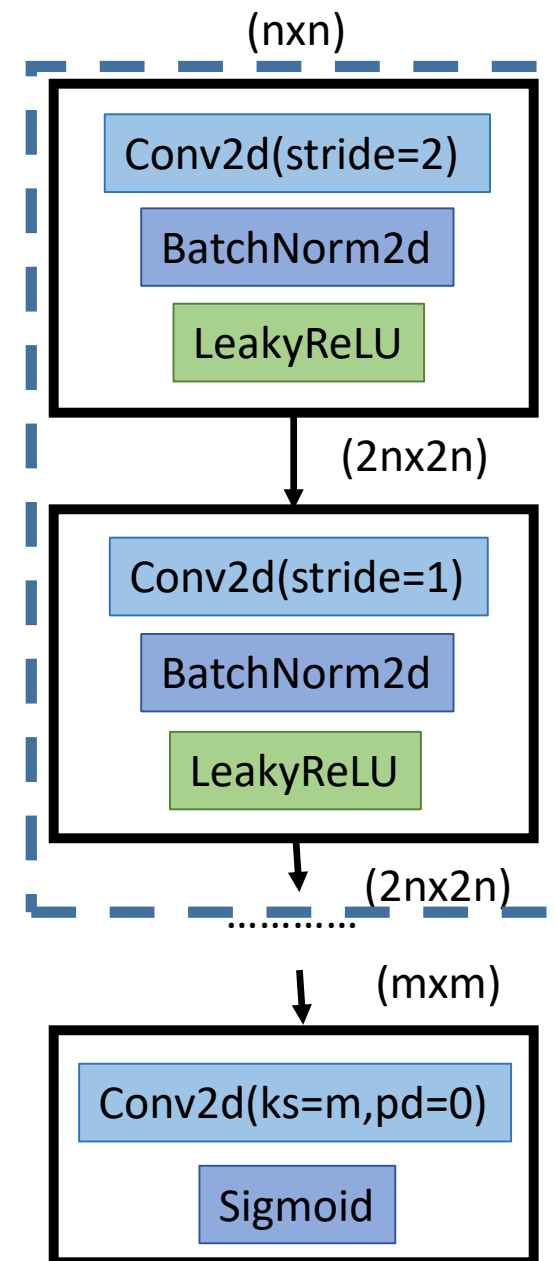
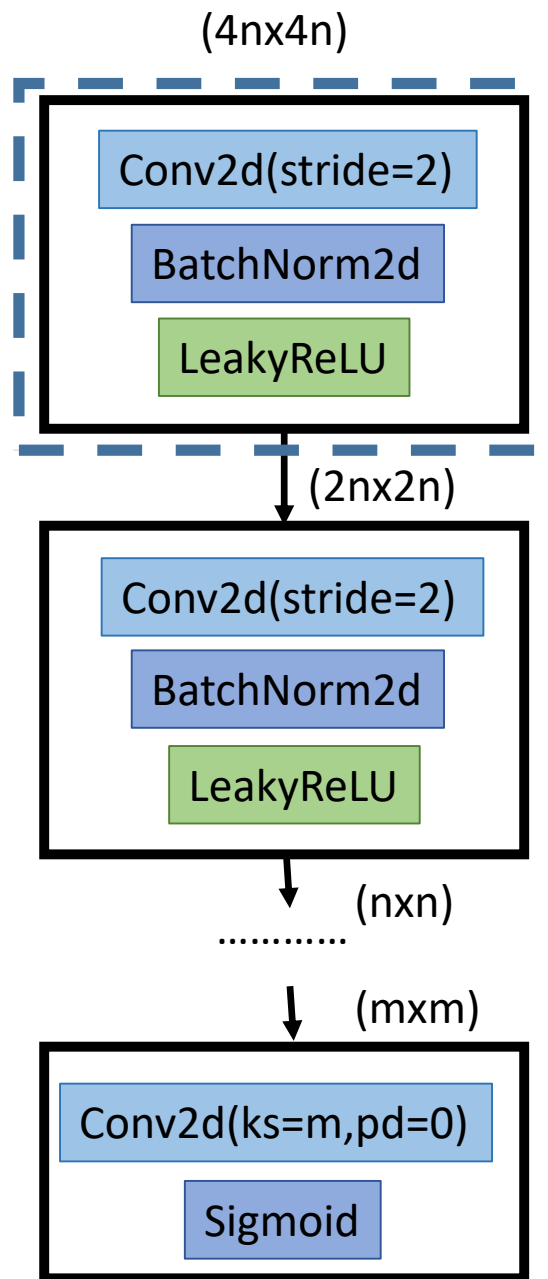
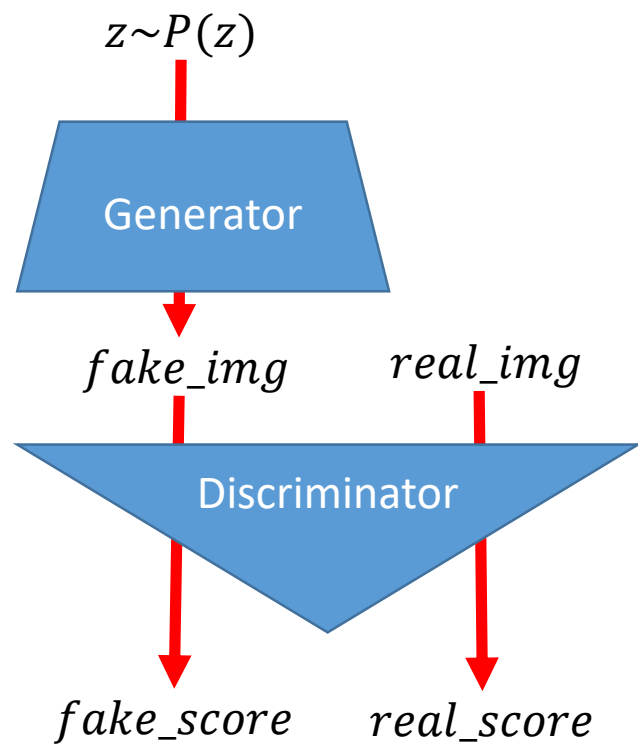
# DCGAN - Generator

example code:

<https://github.com/pytorch/examples/blob/master/dcgan/main.py>

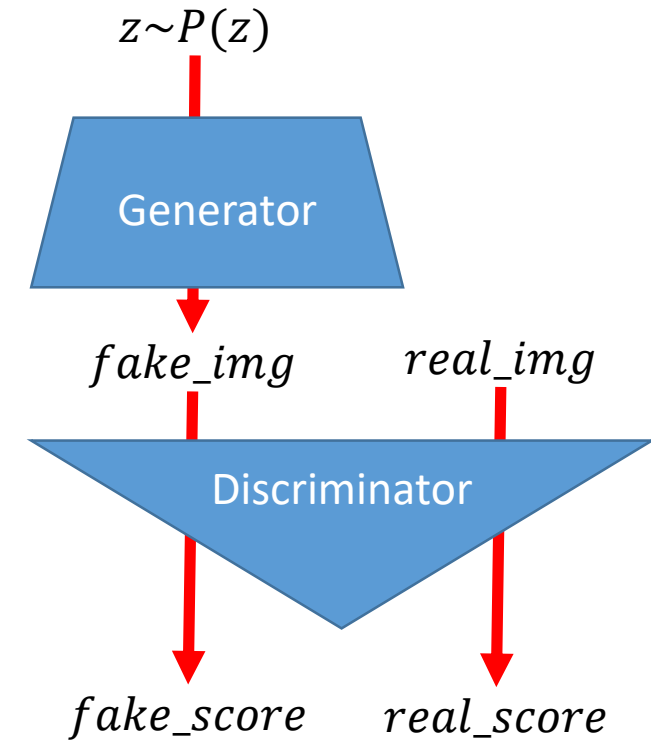


# DCGAN - Discriminator



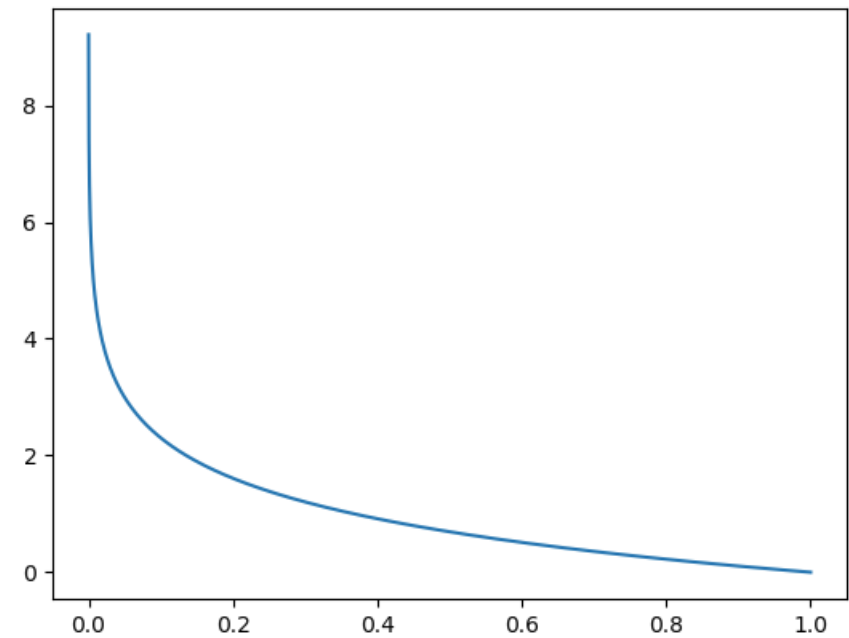
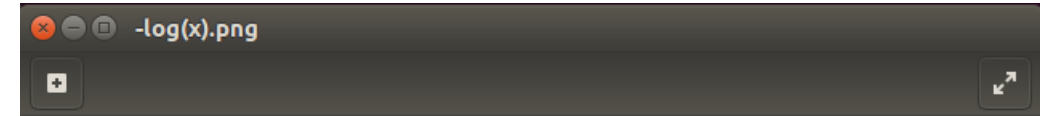
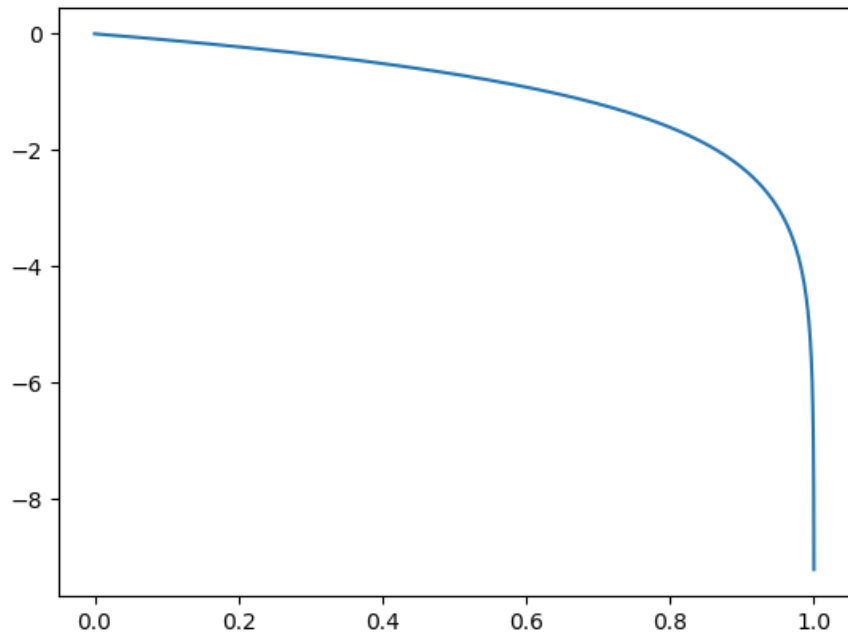
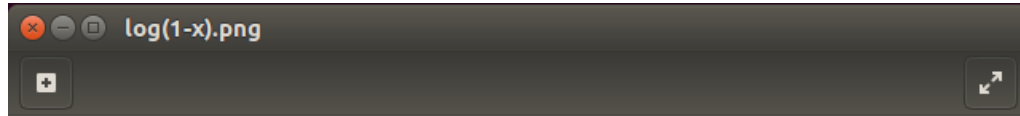
# Standard GAN

$$L_D = -\log(D(I_{real})) - \log(1 - D(G(z)))$$
$$\begin{cases} L_G = \log(1 - D(G(z))) \\ L_G = -\log(D(G(z))) \end{cases}$$

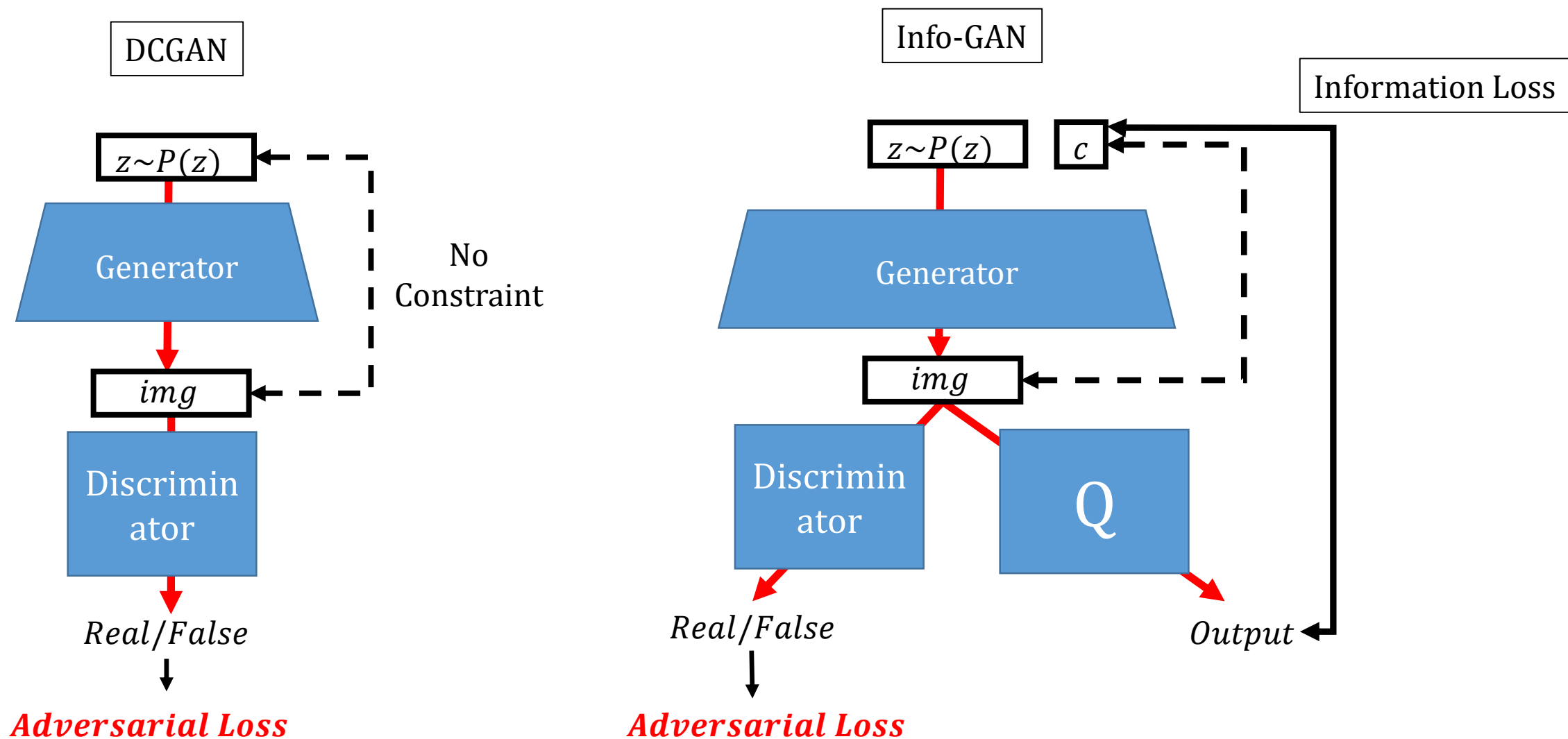


In this lab, you can use either of them, **but you should tell me which one you use in your report.**

# Standard GAN Loss



# Info-GAN



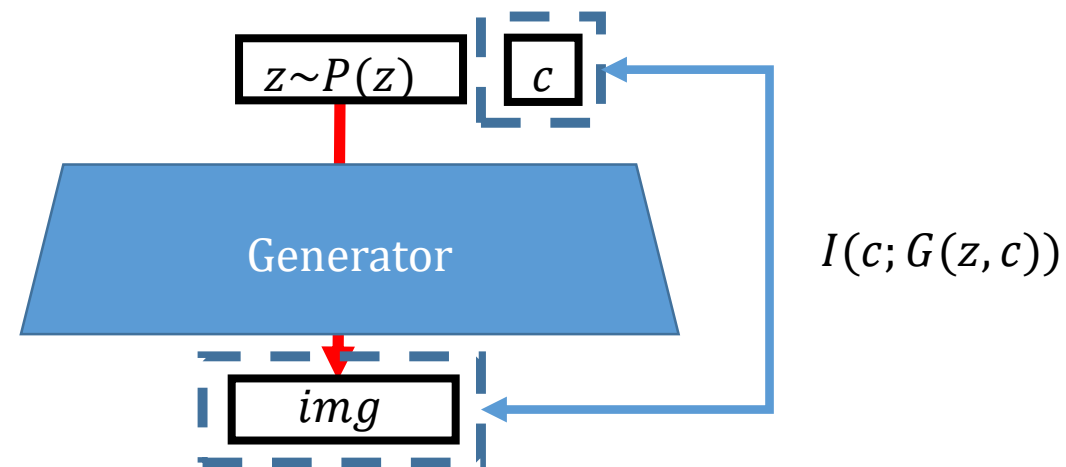
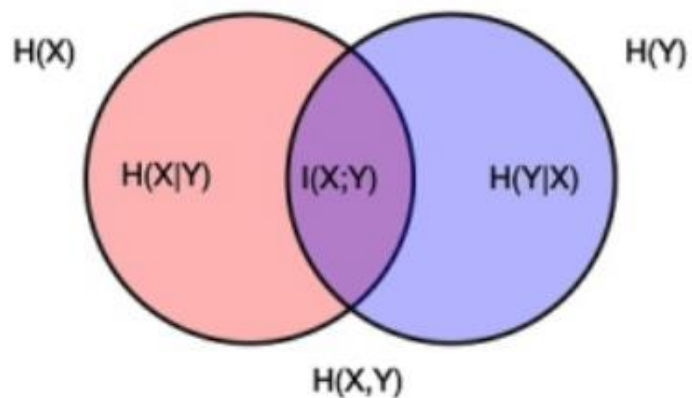
# Info-GAN

In Information Theory:

**Mutual Information:**  $I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$

$$H(Y) = - \sum_y \log p(y)p(y)$$

$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$





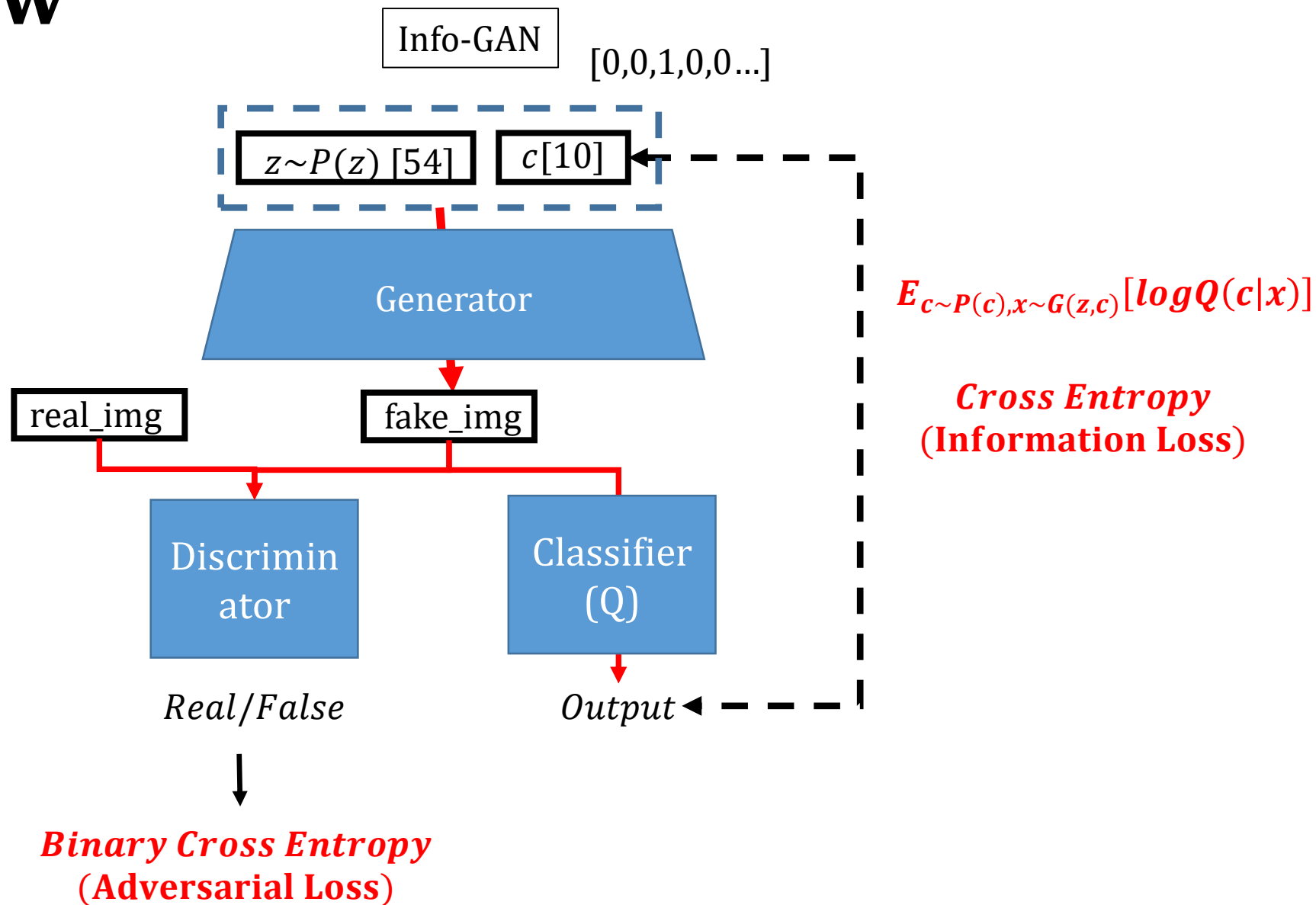
# Info-GAN pf.

$$\begin{aligned} I(c; G(z, c)) &= H(c) - H(c|G(z, c)) \\ &= E_{x \sim G(z, c)} \left[ E_{c' \sim P(c|x)} [\log P(c'|x)] \right] + H(c) \\ &= E_{x \sim G(z, c)} \left[ D_{KL}(P(\cdot | x) || Q(\cdot | x)) + E_{c' \sim P(c|x)} [\log Q(c'|x)] \right] + H(c) \\ &\geq E_{x \sim G(z, c)} \left[ E_{c' \sim P(c|x)} [\log Q(c'|x)] \right] + H(c) \\ &= \mathbf{E_{c \sim P(c), x \sim G(z, c)} [\log Q(c|x)] + H(c)} \end{aligned}$$

We can increase the **lower bound of mutual Information** by other distribution!!

# Info-GAN Flow

Take MNIST for example



# Info-GAN Loss

## *Adversarial Loss*

$$L_D = -\log(D(I_{real})) - \log(1 - D(G(z)))$$

$$\left\{ L_G = \log(1 - D(G(z))) \right.$$

$$\left\{ L_G = -\log(D(G(z))) \right.$$

**Update D  $\Rightarrow$  Update G/Q**

## *Information Loss*

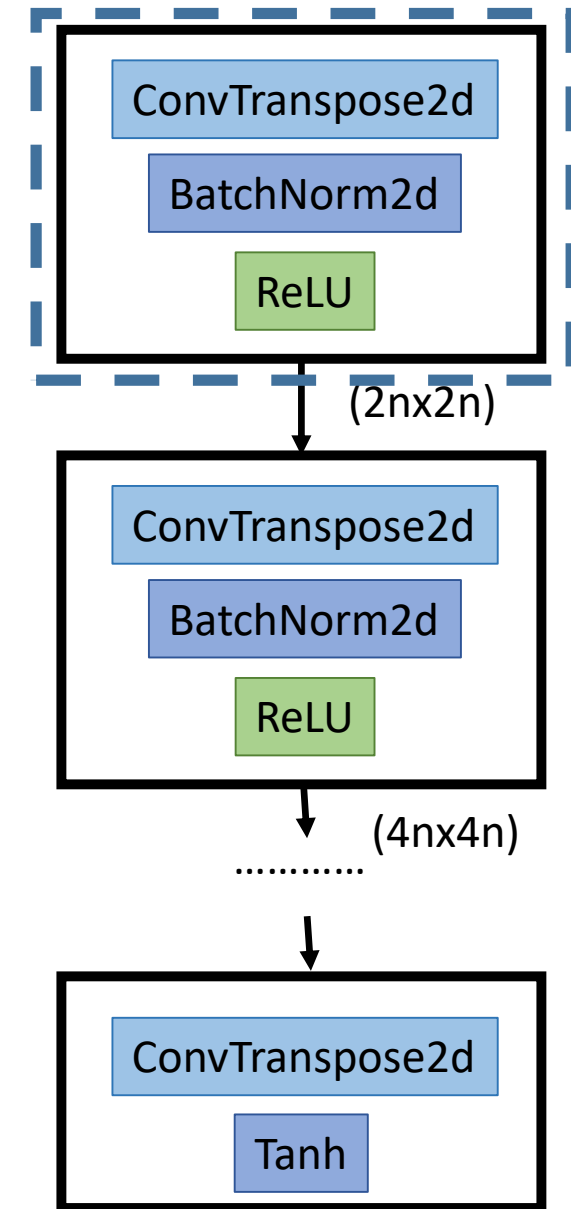
$$L_I(Q, G) = -\log(Q(c|G(z, c)))$$

# Info-GAN Generator

Example code:

<https://github.com/pianomania/infoGAN-pytorch>

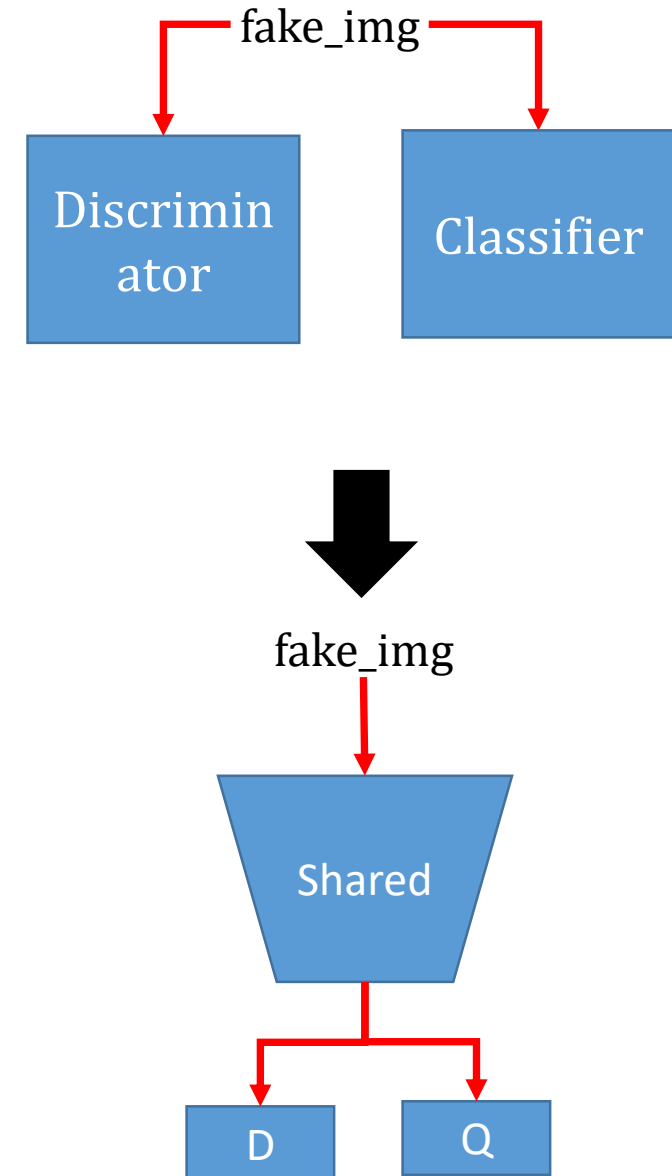
```
_netG(  
  (main): Sequential(  
    (0): ConvTranspose2d(64, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)  
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True)  
    (2): ReLU(inplace)  
    (3): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (4): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True)  
    (5): ReLU(inplace)  
    (6): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (7): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)  
    (8): ReLU(inplace)  
    (9): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True)  
    (11): ReLU(inplace)  
    (12): ConvTranspose2d(64, 1, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (13): Tanh()  
  )  
)
```



# Info-GAN Discriminator

Share weight between D/Q

```
_netD(  
  (main): Sequential(  
    (0): Conv2d(1, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (1): LeakyReLU(0.2, inplace)  
    (2): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)  
    (4): LeakyReLU(0.2, inplace)  
    (5): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True)  
    (7): LeakyReLU(0.2, inplace)  
    (8): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)  
    (9): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True)  
    (10): LeakyReLU(0.2, inplace)  
  )  
  (discriminator): Sequential(  
    (0): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)  
    (1): Sigmoid()  
  )  
  (Q): Sequential(  
    (0): Linear(in_features=8192, out_features=100, bias=True)  
    (1): ReLU()  
    (2): Linear(in_features=100, out_features=10, bias=True)  
  )  
)
```



# Expected Outputs

Expected Outputs

■ Generated images

- More Realistic Output

Different noise  
with the same  
one hot vectors



The same noise with different one hot vectors

# Hyper-parameters

1. Batch size: 64
2. Learning rate for the discriminator:  $2e-4$
3. Learning rate for the generator and Q:  $1e-3$
4. `c_size` (size of meaningful codes) = 10
5. Total epochs = 80
6. Optimizer: Adam

# Info-GAN Report Spec

## MNIST

- 1. Introduction (10%)
- 2. Experiment setups: (20%)
  - A. How you implement InfoGAN
    - i. Adversarial loss
    - ii. Maximizing mutual information
  - B. Which loss function of generator you used? What's different?
- 3. Results (30%)
  - A. Results of your samples (shown as in the expected results section)
  - B. Training loss curves
- 4. Discussion (20%)
- 5. Demo (20%)
  - A. Given a label, you have to generate corresponding images
- (*optional*) Bonus: **Facescrub-5** (15%)
  - Results of your samples (10%)
  - Demo (5%)