# InfoGAN

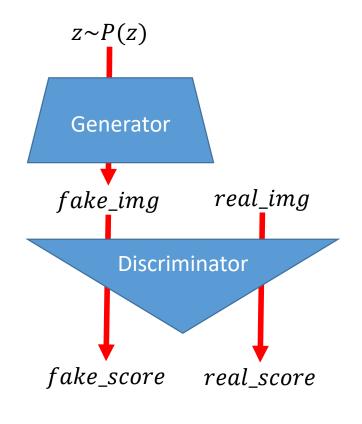
助教:來俊聖

製作: 鄧駿智、來俊聖

## **Standard GAN**

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

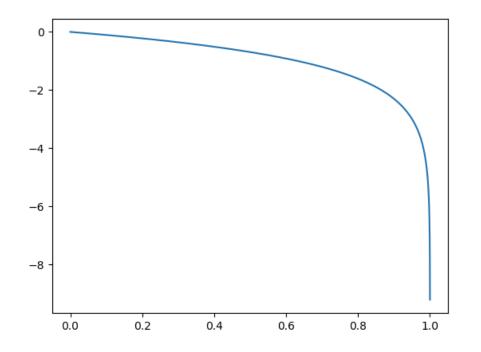
$$\begin{cases} L_G = \log(1 - D(G(z))) \\ L_G = -\log(D(G(z))) \end{cases}$$



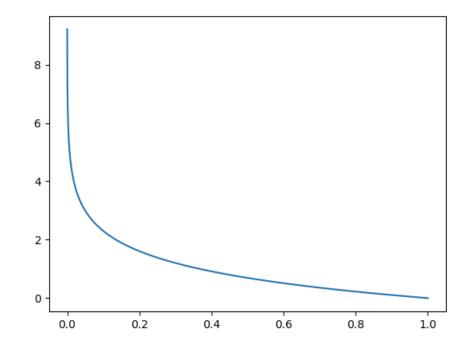
In this lab, you can use either of them, but you should tell me which one you use in your report.

## **Standard GAN Loss**

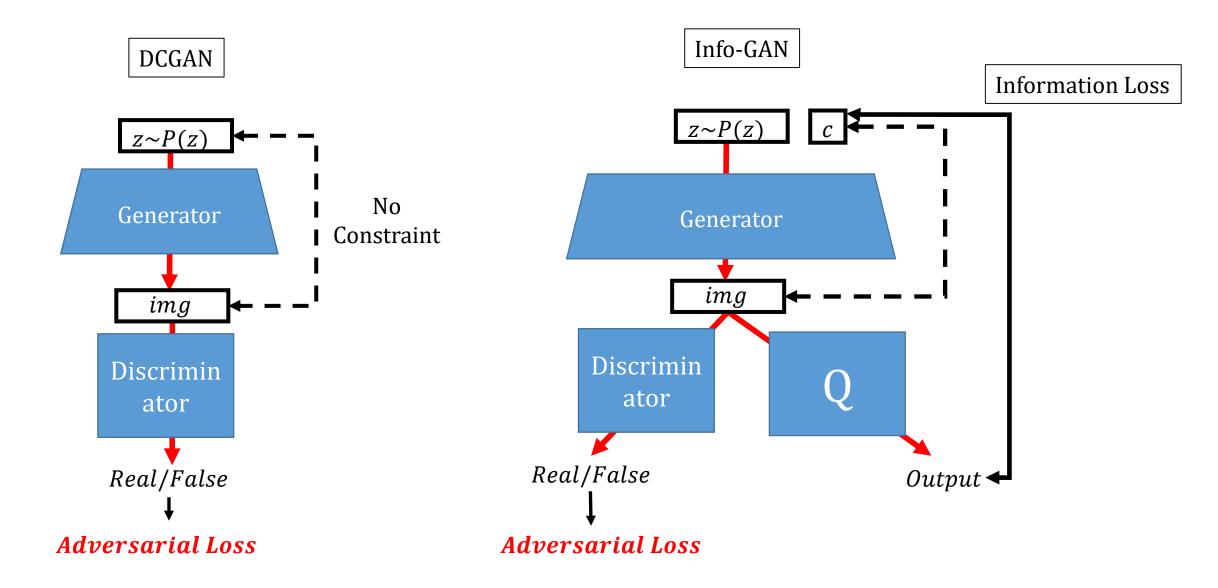








## **Info-GAN**



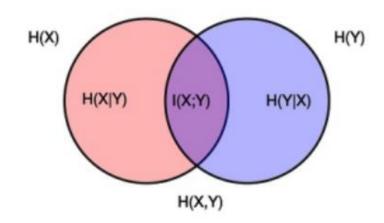
## **Info-GAN**

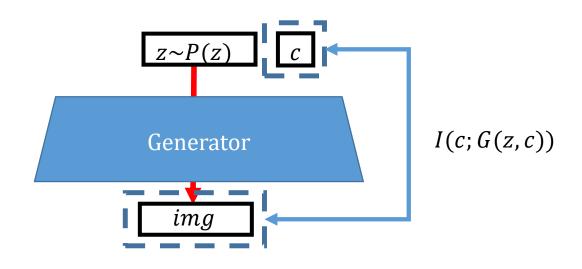
### **In Information Theory:**

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

$$H(Y) = -\sum_{y} \log p(y)p(y)$$

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





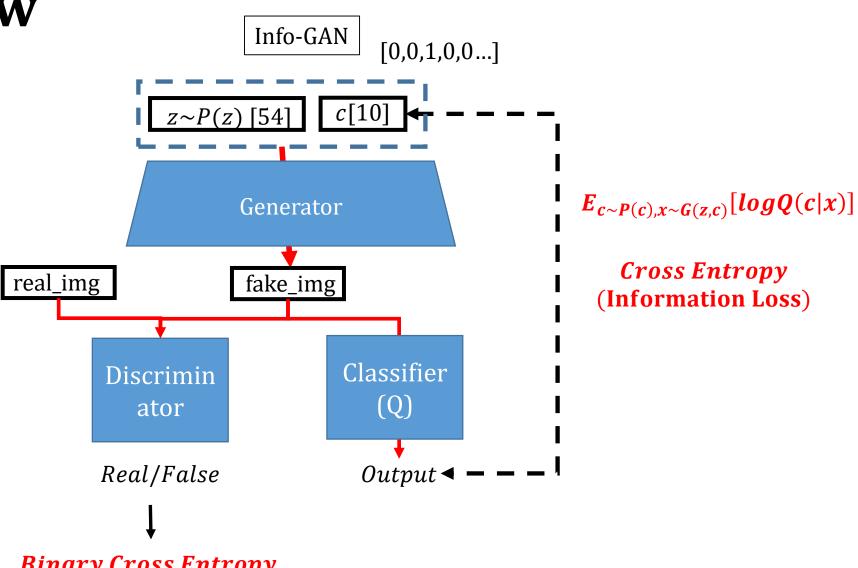
# Info-GAN pf.

$$\begin{split} & \mathrm{I}(\mathsf{c};\mathsf{G}(\mathsf{z},\mathsf{c})) = \mathrm{H}(\mathsf{c}) - \mathrm{H}(\mathsf{c}|\mathsf{G}(\mathsf{z},\mathsf{c})) \\ & = E_{x \sim G(z,c)} \left[ E_{c' \sim P(C|\mathcal{X})} [logP(c'|x)] \right] + \mathrm{H}(\mathsf{c}) \\ & = E_{x \sim G(z,c)} \left[ D_{KL}(P(\cdot|x)||Q(\cdot|x)) + E_{c' \sim P(C|\mathcal{X})} [logQ(c'|x)] \right] + \mathrm{H}(\mathsf{c}) \\ & \geq E_{x \sim G(z,c)} \left[ E_{c' \sim P(C|\mathcal{X})} [logQ(c'|x)] \right] + \mathrm{H}(\mathsf{c}) \\ & = E_{c \sim P(c),x \sim G(z,c)} [logQ(c|x)] + \mathrm{H}(\mathsf{c}) \end{split}$$

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

## **Info-GAN Flow**

Take MNIST for example



Binary Cross Entropy (Adversarial Loss)

## **Info-GAN Loss**

#### Adversarial Loss

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

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

Update  $D \rightleftharpoons Update G/Q$ 

### Information Loss

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

### Pseudo code

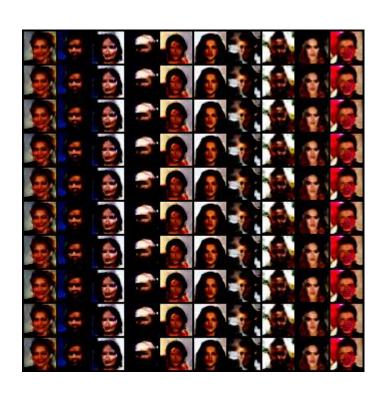
### 1. Update d network

- a. feed real\_image into D network, compute bce loss for D network
- b. Create noise and concatenate with one-hot latent named z
- c. Feed z into the G model and generate fake\_image
- d. Feed fake\_image into D network, compute bce loss for D network

### 2. Update d network

- Generate fake\_image like previously, feed into discriminator and compute bce loss for G network
- b. Feed fake\_image into Q network, then compute classification loss (crossentropy) for G network

# **Expected Outputs**



### To do list

- Complete all model
- Complete training procedure
  - The details are at the pseudo code part.
  - You need to tune learning rate and the weight of each loss at this part.
  - If you are not familiar with this, you are welcome to check sample code online. But please make sure you understand the meaning of all code.

#### Bonus

- At this part, you need to can directly run the training script with a new model for CelebA, but you need to load data yourself.
- Torchvision.datasets.ImageFolder will help, please check it out.

# Hyper-parameters

- mnist
  - 1.  $c_{size} = 10$
  - 2.  $z_{size} = 62$
  - 3. Total epochs = 50
  - 4. Optimizer: Adam
- CelebA
  - 1.  $c_{size} = 100$
  - 2.  $z_{size} = 128$
  - 3. Total epochs = 10
  - 4. Optimizer: Adam
- All other parameters need to be tuned
- You can even change the hyper parameters above

## Important Date

• Deadline: 10/30 11:59 a.m.

• Demo date: 10/30

- Zip report and source code into a .zip file and name it as DLP\_LAB5\_yourlD\_name.zip
- Email to alanlai199.cs07g@nctu.edu.tw with email title DLP\_LAB5\_yourID\_name

# 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
  - B. Training loss curves
- 4. Discussion (20%)
- 5. Demo (20%)
  - Show your result and explain your code
- (optional) Bonus: CelebA (15%)
  - Results of your samples (10%)
  - Demo (5%)