# Label 4: Info GAN

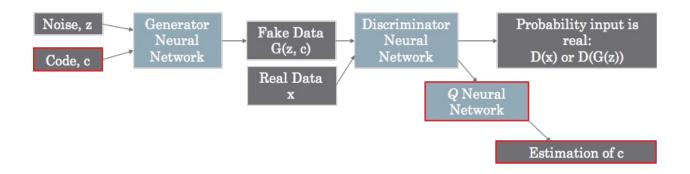
## **Outline**

- 1. Introduction
- 2. Experiment setups
- 3. Experiment results
- 4. Discussion

### 1. Introduction

運用擁有可以找到隱藏 code 與數據關係的抗式網路架構, 搭配 MNIST 資料訓練出用特定的 code 可以輸出特定的 MNIST 數字圖片。

#### 網路架構:



#### 目標公式:

$$\min_{G,Q} \max_{D} V_{InfoGAN}(D, G, Q) = V(D, G) - \lambda L_I(G, Q)$$

$$L_1(G,Q) = E_{c \sim P(c), x \sim G(z,c)}[\log Q(c \mid x)] + H(c)$$

## 2. Experiment setups

#### Setups:

beta1, beta2: 控制 Adam 計算梯度及平方的運行平均值的係數。 criterion\_q\_continous: 計算 code 對資料的 loss。

```
batch_size = 64
epoch = 100
learning_rate = 1e-4
beta1 = 5e-1
beta2 = 999e-3
```

```
class NormalNLLLoss:

def __call__(self, x, mu, var):
    logli = -0.5 * (var.mul(2 * np.pi) + 1e-6).log() - (x - mu).pow(2).div(var.mul(2.0) + 1e-6)
    return -(logli.sum(1).mean())
```

**Generator**: 加厚了一組的 ConvTranspose2d,以及 activation 改用 LeakyReLU。

```
class Generator(nn.Module):
   def init (self):
       super(). init ()
       self.generator = nn.Sequential(
           nn.ConvTranspose2d(74, 512, 1, 1, bias = False),
           nn.BatchNorm2d(512),
           nn.LeakyReLU(),
           nn.ConvTranspose2d(512, 1024, 1, 1, bias = False),
           nn.BatchNorm2d(1024),
           nn.LeakyReLU(),
           nn.ConvTranspose2d(1024, 128, 7, 1, bias = False),
           nn.BatchNorm2d(128),
           nn.LeakyReLU(),
           nn.ConvTranspose2d(128, 64, 4, 2, padding = 1, bias = False),
           nn.BatchNorm2d(64),
           nn.LeakyReLU(),
           nn.ConvTranspose2d(64, 1, 4, 2, padding = 1, bias = False),
           nn.Sigmoid()
   def forward(self, input):
       return self.generator(input)
```

#### Discriminator:

```
class Discriminator(nn.Module):
    def __init__(self):
        super().__init__()
        self.discriminator = nn.Sequential(
            nn.Conv2d(1, 64, 4, 2, 1),
            nn.LeakyReLU(0.1, True),

            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.1, True),

            nn.Conv2d(128, 1024, 7, bias = False),
            nn.BatchNorm2d(1024),
            nn.LeakyReLU(0.1, True)
            )
            def forward(self, input):
            return self.discriminator(input)
```

DHead: 加厚一層 Conv2d 以及搭配一個 Sigmoid。

#### QHead:

```
class QHead(nn.Module):
    def __init__(self):
        super().__init__()

    self.conv1 = nn.Conv2d(1024, 128, 1, bias=False)
    self.bn1 = nn.BatchNorm2d(128)
    self.leakyReLU = nn.LeakyReLU(0.1, True)

    self.conv_disc = nn.Conv2d(128, 10, 1)
    self.conv_mu = nn.Conv2d(128, 2, 1)
    self.conv_var = nn.Conv2d(128, 2, 1)

def forward(self, x):
    x = self.leakyReLU(self.bn1(self.conv1(x)))

    disc_logits = self.conv_disc(x).squeeze()
    war = torch.exp(self.conv_var(x).squeeze())
    return disc_logits, mu, var
```

#### InfoGAN: 組合以上 Model。

```
lass InfoGAN(nn.Module):
  def init (self, device):
      super(). init ()
      self.generator = Generator().to(device)
      self.generator.apply(self.weights init)
      self.discriminator = Discriminator().to(device)
      self.discriminator.apply(self.weights init)
      self.qHead = QHead().to(device)
      self.qHead.apply(self.weights init)
      self.dHead = DHead().to(device)
      self.dHead.apply(self.weights init)
  def forward realData(self, inputs):
      outputs = self.discriminator(inputs)
      return self.dHead(outputs).view(-1)
  def forward noise(self, noise):
       fake data = self.generator (noise)
      outputs = self.discriminator(fake data.detach())
      probs fake = self.dHead(outputs).view(-1)
      return fake data, probs fake
  def foward fake data treated as real(self, fake data):
      output treated = self.discriminator(fake data)
      probs treated = self.dHead(output treated).view(-1)
      return output treated, probs treated
  def foward treated data to Q(self, treated data):
      return self.qHead(treated data)
  def foward genImage(self, fixed noise):
       return self.generator(fixed noise).detach().cpu()
  def weights init(self, model):
       if(type(model) == nn.ConvTranspose2d or type(model) == nn.Conv2d):
          nn.init.normal (model.weight.data, 0.0, 0.02)
      elif(type(model) == nn.BatchNorm2d):
          nn.init.normal (model.weight.data, 1.0, 0.02)
          nn.init.constant (model.bias.data, 0)
```

#### DataTransformer: 生成 MNIST 以及測試用的 fixed noise 與訓練

用的 noise sample 和 Label 腳本。

```
class DataTransformer:
    def __init__(self, use_cuda):
        self.root = "./Datasets/"
        self.use_cuda = use_cuda

        self.num_z = 62
        self.num_dis_c = 1
        self.dis_c_dim = 10
        self.num_con_c = 2

        self.real_label = 1
        self.fake_label = 0

def get_dataloader(self, batch_size):
        transform = transforms.Compose([transforms.Resize(28), transforms.CenterCrop(28), transforms.ToTensor()])
        dataset = datasets.MNIST(self.root, train = 'train', download = True, transform = transform)
        dataloader = torch.utils.data.DataLoader(dataset, batch_size = batch_size, shuffle = True)
        return dataloader
```

```
def fixedNoise(self, count = 100, number = None):
    fixed noise = torch.randn(count, self.num z, 1, 1)
    if number == None:
        idx = np.arange(self.dis c dim).repeat(10)
    else:
        number = [self.changeIndex(number[x]) for x in range(len(number))]
        idx = number
    dis c = torch.zeros(count, self.num dis c, self.dis c dim)
    for i in range(self.num dis c):
        dis c[torch.arange(0, count), i, idx] = 1.0
    dis c = dis c.view(count, -1, 1, 1)
    con c = torch.rand(count, self.num con c, 1, 1) * 2 - 1
    fixed noise = torch.cat((fixed noise, dis c), 1)
    fixed noise = torch.cat((fixed noise, con c), 1)
    if self.use cuda:
        fixed noise = fixed noise.cuda()
    return fixed noise
```

```
def getNoiseSample(self, batch_size):
    z = torch.randn(batch_size, self.num_z, 1, 1)
    idx = np.zeros((self.num_dis_c, batch_size))
    dis_c = torch.zeros(batch_size, self.num_dis_c, self.dis_c_dim)

for i in range(self.num_dis_c):
    idx[i] = np.random.randint(self.dis_c_dim, size = batch_size)
    dis_c[torch.arange(0, batch_size), i, idx[i]] = 1.0
    dis_c = dis_c.view(batch_size, -1, 1, 1)

con_c = torch.rand(batch_size, self.num_con_c, 1, 1) * 2 - 1

z = torch.cat((z, dis_c), 1)
    z = torch.cat((z, con_c), 1)

if self.use_cuda:
    z = z.cuda()

return z, idx
```

```
def getRealLabel(self, size):
    label = torch.full((size, ), self.real_label)
    if self.use_cuda:
        label = label.cuda()
    return label

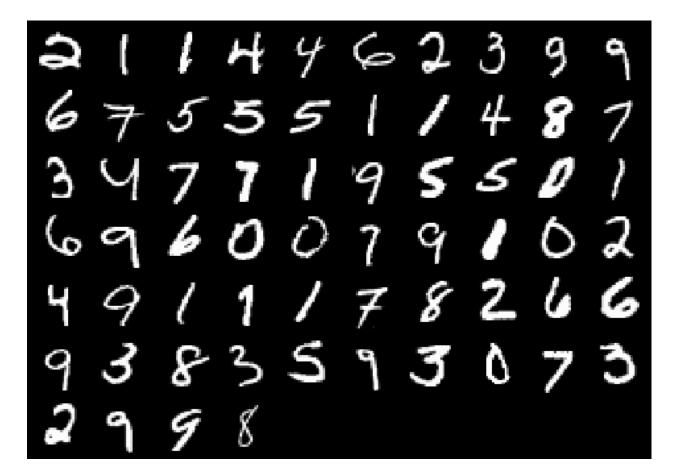
def getFakeLabel(self, real_label):
    return real_label.clone().fill_(self.fake_label)
```

#### Train: 藍色框針對訓練 discriminator, 紅色框框針對 generator 訓

練。

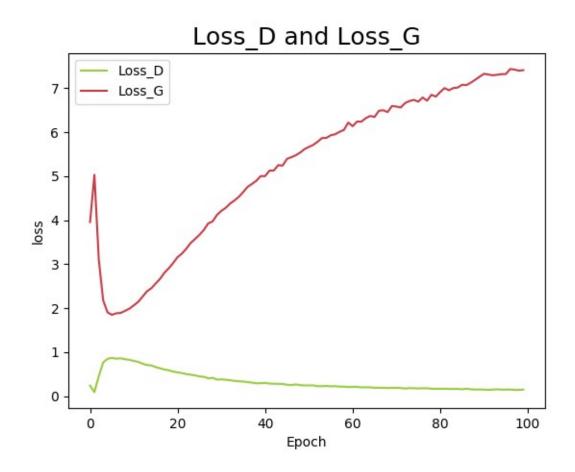
```
for e in range(1, epoch + 1):
    model.changeToTrainMode()
   D losses = 0
   G losses = 0
   for times, (real data, ) in enumerate(dataloader, 0):
       real data size = real data.size(0)
       if use cuda:
          real data = real data.cuda()
       optimizer_discriminator.zero_grad()
       real_label = dataTransfomer.getRealLabel(real_data_size)
       output_real = model.forward_realData(real_data)
       loss_real = criterion_discriminator(output_real, real_label)
        loss_real.backward()
        fake_label = dataTransfomer.getFakeLabel(real_label)
       noise, idx = dataTransfomer.getNoiseSample(real_data_size)
        fake_data, probs_fake = model.forward_noise(noise)
        loss_fake = criterion_discriminator(probs_fake, fake_label)
        loss fake.backward()
       D loss = loss real + loss fake
       optimizer_discriminator.step()
       optimizer_generator.zero_grad()
       output_treated, probs_treated = model.foward_fake_data_treated_as_real(fake_data)
       loss_gen = criterion_discriminator(probs_treated, real_label)
       q_logits, q_mu, q_var = model.foward_treated_data_to_Q(output_treated)
        target = torch.LongTensor(idx).to(device)
       dis_loss = 0
        for x in range(dataTransfomer.num_dis_c):
           noise[:, dataTransfomer.num_z + dataTransfomer.num_dis_c * dataTransfomer.dis_c_dim :].view(-1, dataTransfomer.num_con_c)
       G_loss = loss_gen + dis_loss + con_loss
       G loss.backward()
       optimizer generator.step()
       G losses += G loss.item()
       D_losses += D_loss.item()
       \overline{if} times % 10\overline{0} == 0:
           print('[%d/%d][%d/%d]' %(e, epoch, times, len(dataloader)))
   D losses /= times
```

### **Training Image:**



# 3. Experiment results

**Training situation**: 會發現 LossD 與 LossG 前面會彼此靠近後開始相差越來越遠



### **Prdict in training:**



**Testing**: 輸入[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

0123456789

## 4. Discussion

從 Loss 曲線圖發現,以及實際 predict 出來的,越往後面的訓練 LossD 與 LossG 的訓練成效就不會有太大的改變或是越來越糟糕,可能是因為 Discriminator 越來越強,導致 Generator 的訓練變得隨便都可以過。

