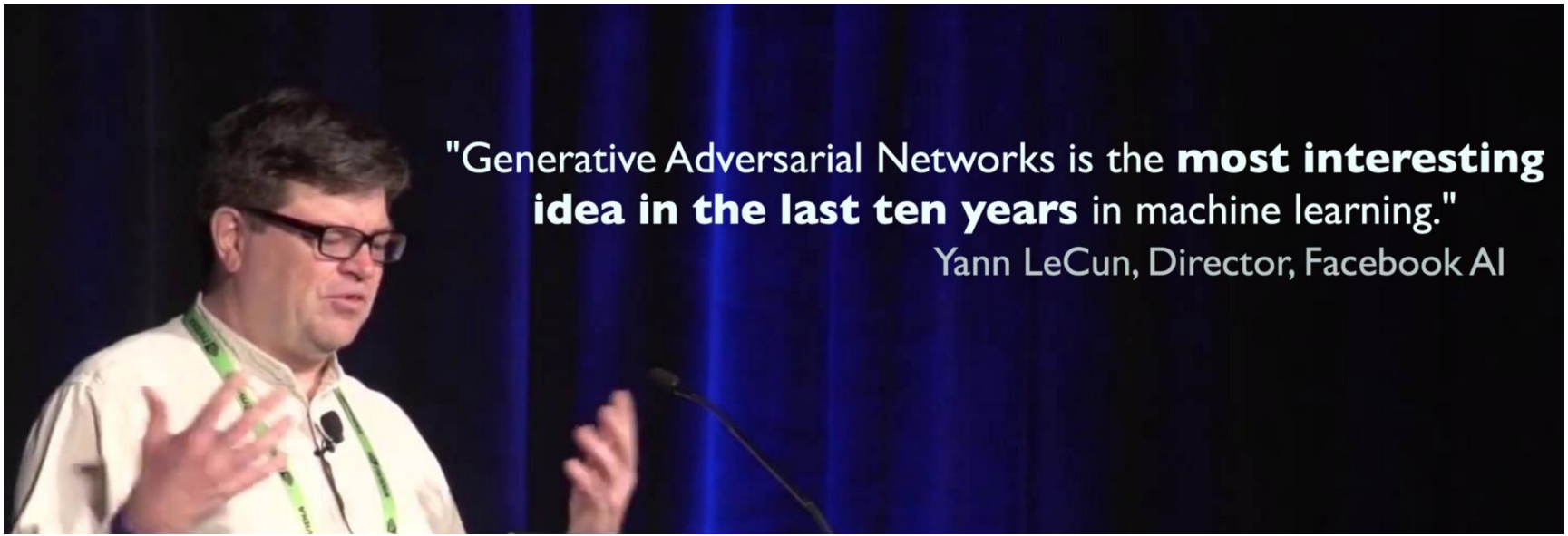
Generative Adversarial Networks

2017.12.09

최건호

INDEX

Basic Concept



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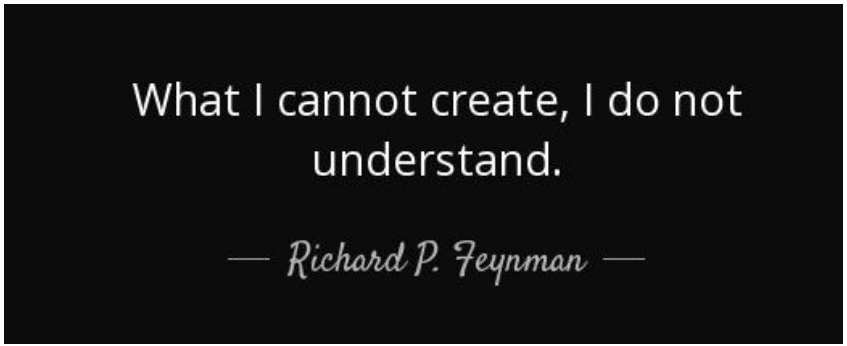
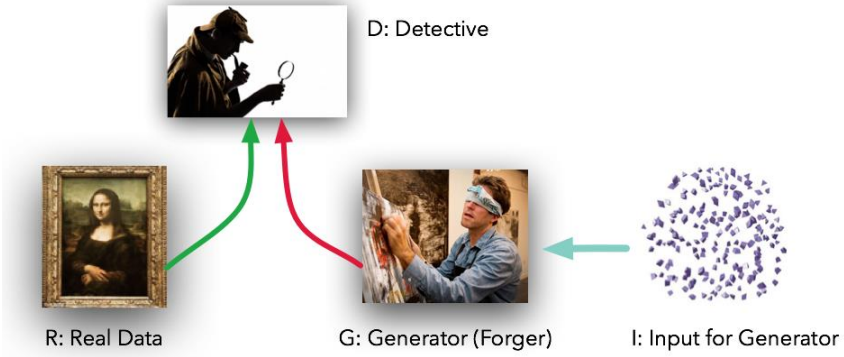
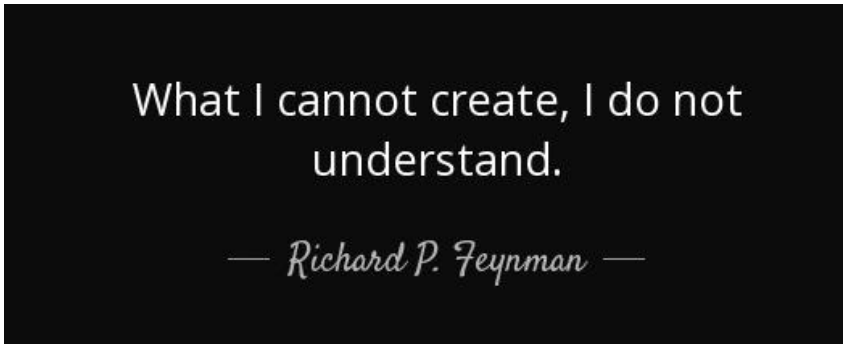


Generative Model은 스스로 데이터를 생성해내는 모델. 어떤 데이터를 보고 분류하는 것 보다 그 데이터를 만들어 -내는 것이 더 어려움.
ex) GAN, VAE

Basic Concept



Generative Adversarial Networks



https://medium.com/@devnag/generative-adversarial-networks-gans-in-50-lines-of-code-pytorch-e81b79659e3f

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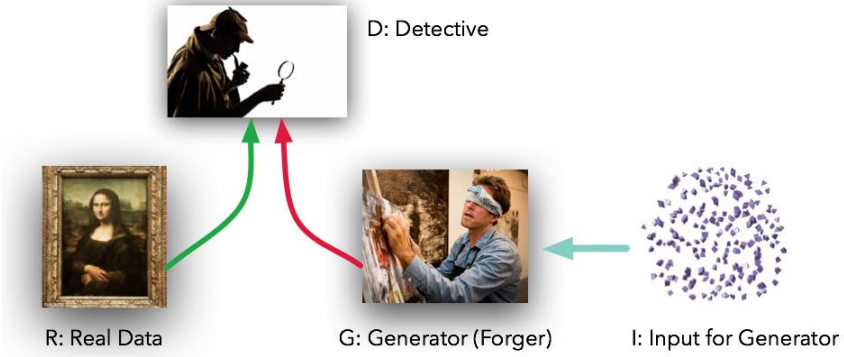
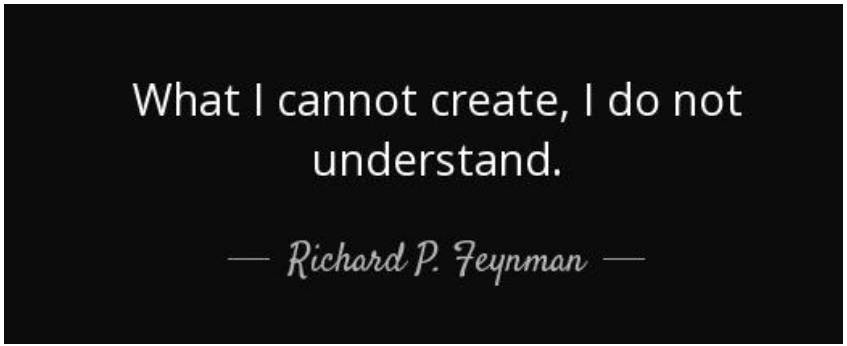
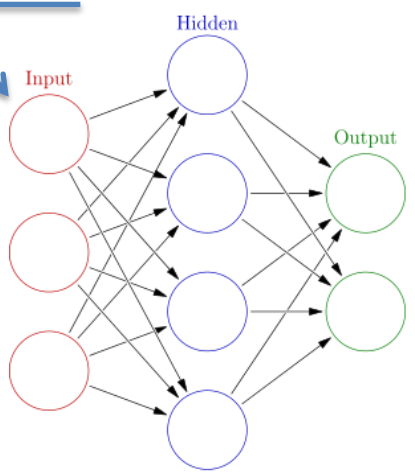


Generative Adversarial Networks





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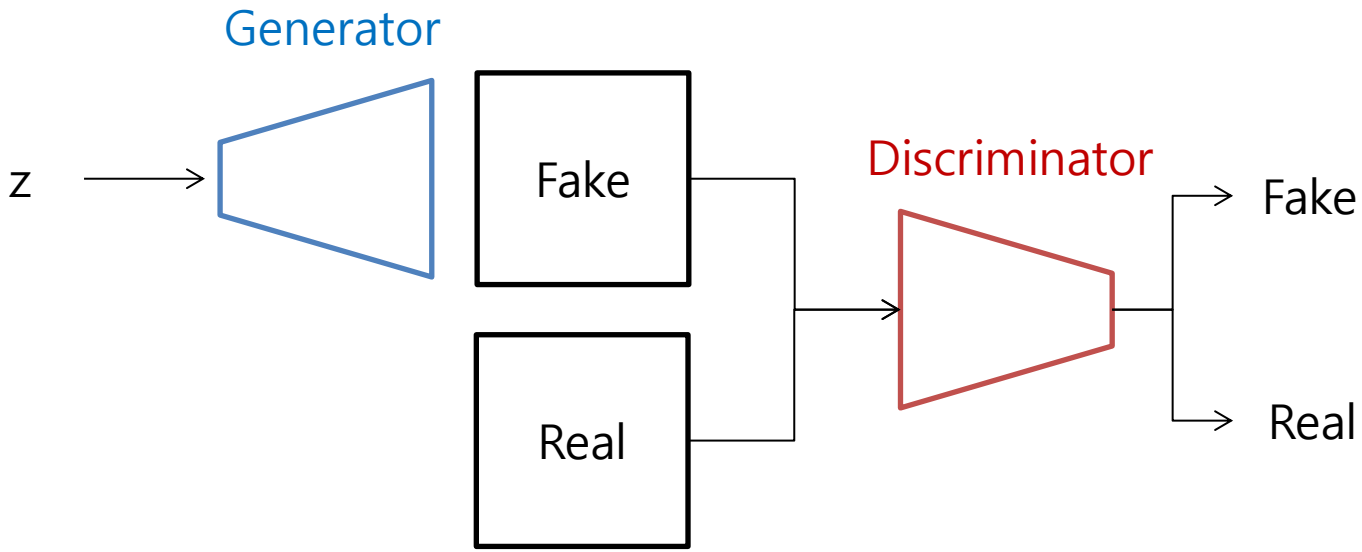

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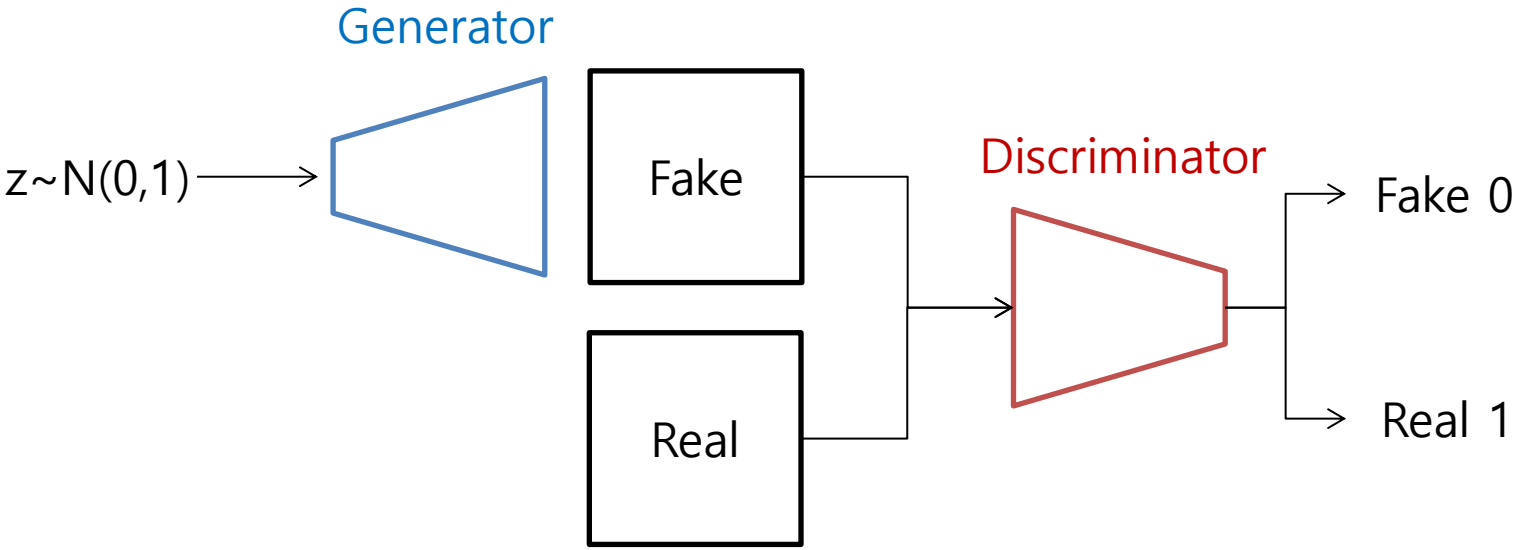

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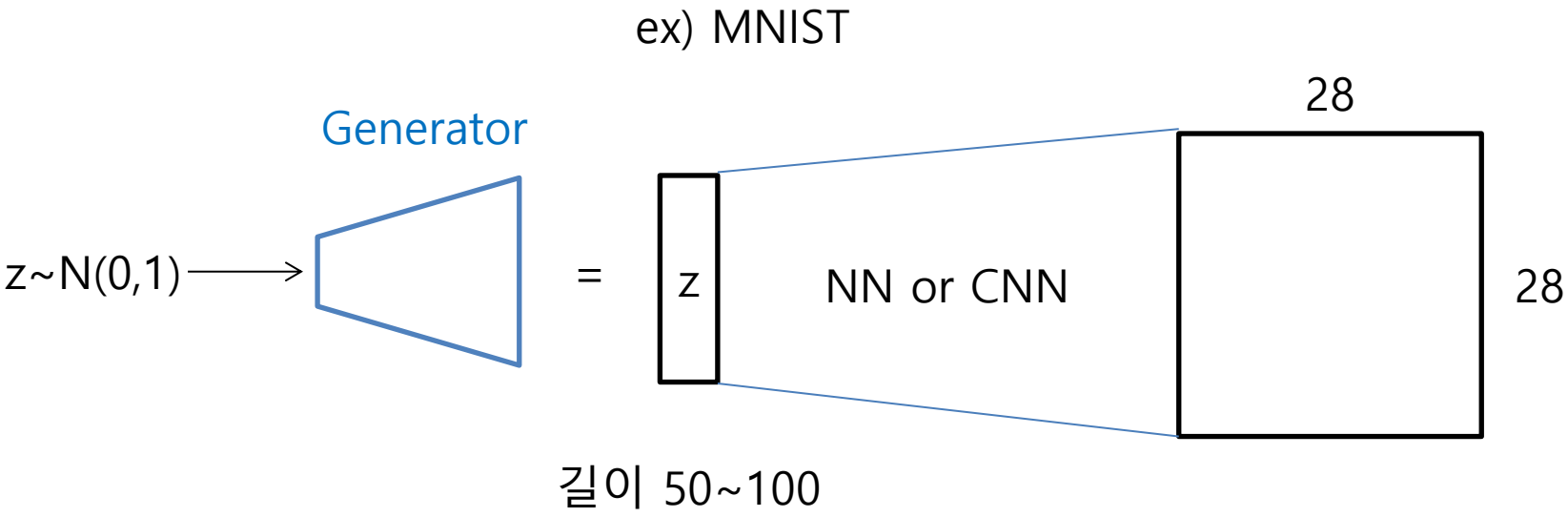
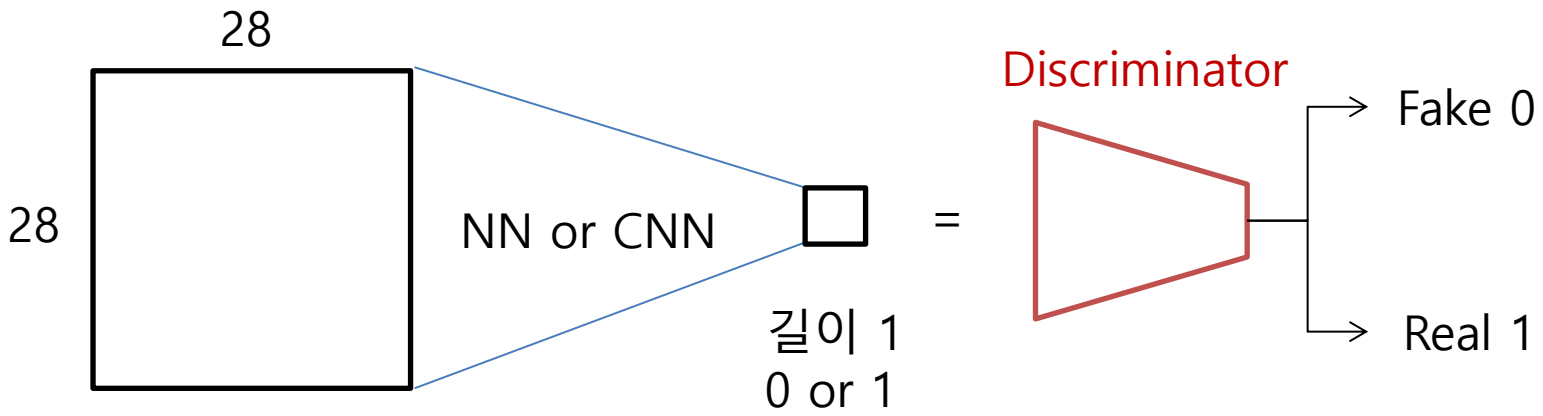


Basic Concept

ex) MNIST



Basic Concept

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

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Generator: 전체 값이 최소가 되는 G를 찾아야 하기 때문에 $1 - D\big(G(z)\big)$값이 작아야 함. 즉, G가 만들어낸 데이터에 대해 D가 1(real data)라고 판단하도록 학습.

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Discriminator: 전체 값이 최대가 되는 D를 찾아야 하기 때문에 진짜 데이터 x -에 대해서는 1(real data)을 출력하고 $D\big(G(z)\big)$에 대해서는 0을 출력하도록 학습.

Basic Concept

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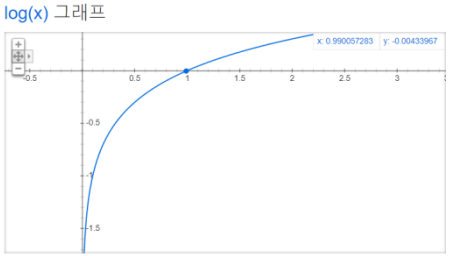
D, G에 대해서 분리

Basic Concept



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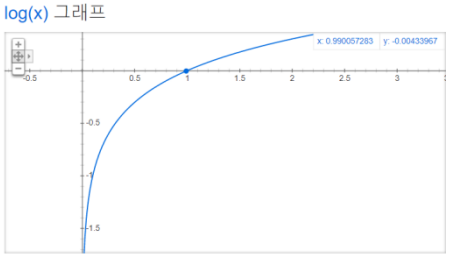

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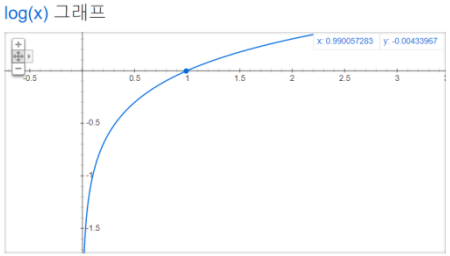

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$D(\boldsymbol{x})$: 1 (0) — $D(G(\boldsymbol{z}))$: 0 (1)

Best case: 0+0=0

Worst case: $-\infty + (-\infty) = -\infty$

Basic Concept

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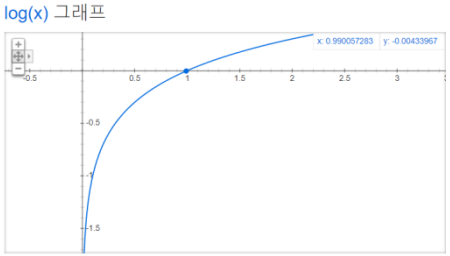

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0
1

Best case: -∞
Worst case: 0

Basic Concept

조금만 더 자세히
Discriminator부터

$$\max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

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최대값을 찾자
D(x)에 대해 미분해서 0이 나오는 지점을 찾으면 됨

Basic Concept

$$P_{data}(x)[logD(x)] + P_g(x)[\log(1 - D(x))]$$

$$D(x) = \ y$$
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$$\frac{a - ay - by}{y(1 - y)} = \frac{a - y(a + b)}{y(1 - y)} = 0$$

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실제 데이터와 생성된 데이터를 구분할 수 없을 때 D(x)=0.5

Basic Concept

$$D^*(x) = \frac{P_{data}(x)}{P_{data}(x)+P_g(x)}$$

현재 D(x)가 optimal이라고 가정하고 아래의 식을 풀면?

$$\min_G V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

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$$= -log4 + \int_x P_{data}(x)log\frac{2*P_{data}(x)}{P_{data}(x)+P_g(x)}dx + \int_x P_g(x)log\frac{2*P_g(x)}{P_{data}(x)+P_g(x)}dx$$

Basic Concept

$$= -log4 + \int_x P_{data}(x) log \frac{P_{data}(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx + \int_x P_g(x) log \frac{P_g(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx$$

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$$= -log4 + KL\left(P_{data}(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right) + KL\left(P_g(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right)$$

Basic Concept

$$= -log4 + \int_x P_{data}(x) log \frac{P_{data}(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx + \int_x P_g(x) log \frac{P_g(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx$$

$$= -log4 + KL\left(P_{data}(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right) + KL\left(P_g(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right)$$

<Jensen-Shannon Divergence>

$$\frac{1}{2} KL(P \| M) + \frac{1}{2} KL(Q \| M)$$

$$\text{where } KL(A \| B) = \sum_i^N a_i \ln \frac{a_i}{b_i}$$

$$M = \frac{1}{2}(P + Q)$$

Basic Concept

$$= -log4 + \int_x P_{data}(x) log \frac{P_{data}(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx + \int_x P_g(x) log \frac{P_g(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx$$

$$= -log4 + KL\left(P_{data}(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right) + KL\left(P_g(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right)$$

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$$= -log4 + 2JS\left(P_{data}(x) \middle\| P_g(x)\right)$$

Basic Concept

$$= -log4 + \int_x P_{data}(x) log \frac{P_{data}(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx + \int_x P_g(x) log \frac{P_g(x)}{\frac{P_{data}(x) + P_g(x)}{2}} dx$$

$$= -log4 + KL\left(P_{data}(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right) + KL\left(P_g(x) \middle\| \frac{P_{data}(x) + P_g(x)}{2}\right)$$

$$= -log4 + 2JS\left(P_{data}(x) \| P_g(x)\right)$$

$JS \geq 0$, $P_{data}(x) = P_g(x)$일때 0이므로 원래의 식을 minimize하는 $P_g(x)$ 는 $P_{data}(x)$와 같은 분포를 가지게 된다.

Basic Concept

$$\max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

$$\min_G V(D,G) = \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Basic Concept

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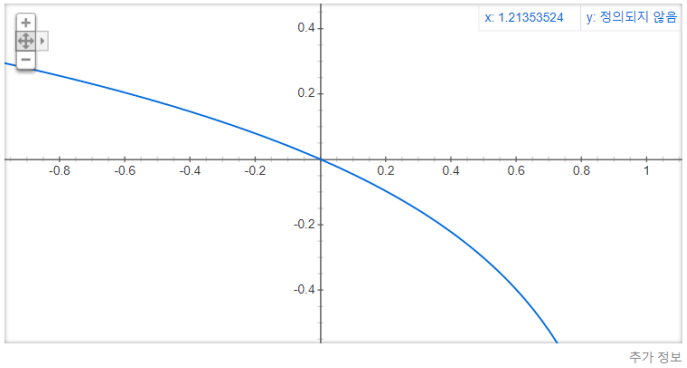
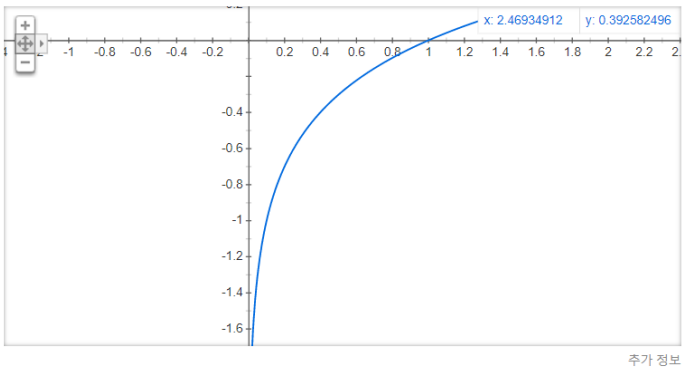
$$\min_G V(D,G) = \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

사실 $\log\left(1 - \mathrm{D}\left(\mathrm{G}(\mathrm{z})\right)\right)$를 최소화하는것은 $\log\left(D\left(G(z)\right)\right)$를 $maximize$ 하는것과 같음
같은 의미지만 후자의 gradient값들이 더 크기 때문에 학습이 더 잘됨

log(1-x) 그래프



log(x) 그래프



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$$\max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

1 0

$$\max_G V(D,G) = \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(D(G(\boldsymbol{z})))].$$

1

Basic Concept

$$\max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log \underbrace{D(\boldsymbol{x})}_{1}] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - \underbrace{D(G(\boldsymbol{z}))}_{0})].$$

$$\max_G V(D,G) = \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(\underbrace{D(G(\boldsymbol{z}))}_{1})].$$

label이 0 또는 1이기 때문에 구현할 때는 binary cross entropy loss 사용

class **torch.nn.BCELoss**(*weight=None, size_average=True*) [source]

Creates a criterion that measures the Binary Cross Entropy between the target and the output:

$$loss(o,t) = -1/n \sum_i (t[i] * log(o[i]) + (1 - t[i]) * log(1 - o[i]))$$

Basic Concept

학습이 잘 되면 Discriminator의 결과값은 0.5로 수렴하게 됨
결과값이 0.5라는 것은 진짜인지 아닌지 구별이 불가능한 상태

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하지만 이 값만으로는 Generator가 잘 학습해서 속이는 것인지
아니면 Discriminator가 아직 구분을 잘 못하는 것인지 알 수 없음

Basic Concept

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아직까지는 general metric 이 없어서 눈 discriminator가 사용됨

Basic Concept

```
class Generator(nn.Module):
    def __init__(self):
        super(Generator,self).__init__()
        self.layer1 = nn.Linear(100,7*7*256)
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,3,2,1,1)),
                ('relu1', nn.LeakyReLU()),
                ('bn1', nn.BatchNorm2d(128)),
                ('conv2', nn.ConvTranspose2d(128,64,3,1,1)),
                ('relu2', nn.LeakyReLU()),
                ('bn2', nn.BatchNorm2d(64))
            ]))
        self.layer3 = nn.Sequential(OrderedDict([
                ('conv3',nn.ConvTranspose2d(64,16,3,1,1)),
                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(16)),
                ('conv4',nn.ConvTranspose2d(16,1,3,2,1,1)),
                ('relu4',nn.LeakyReLU())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Basic Concept

size 100인 Noise z에서
7*7*256 크기로 늘림

```
class Generator(nn.Module):
    def __init__(self):
        super(Generator,self).__init__()
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                ('bn1', nn.BatchNorm2d(128)),
                ('conv2', nn.ConvTranspose2d(128,64,3,1,1)),
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                ('bn2', nn.BatchNorm2d(64))
            ]))
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```

Basic Concept

size 100인 Noise z에서
7*7*256 크기로 늘림

Autoencoder였으면 decoder
부분에 해당하는 generator

```
class Generator(nn.Module):
    def __init__(self):
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                ('conv2', nn.ConvTranspose2d(128,64,3,1,1)),
                ('relu2', nn.LeakyReLU()),
                ('bn2', nn.BatchNorm2d(64))
            ]))
        self.layer3 = nn.Sequential(OrderedDict([
                ('conv3',nn.ConvTranspose2d(64,16,3,1,1)),
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                ('bn3',nn.BatchNorm2d(16)),
                ('conv4',nn.ConvTranspose2d(16,1,3,2,1,1)),
                ('relu4',nn.LeakyReLU())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Basic Concept

size 100인 Noise z에서
7*7*256 크기로 늘림

Autoencoder였으면 decoder 부분에 해당하는 generator

nn.Sequential 안에 layer 이름을 지정할 수 있게 OrderedDict를 사용함

```
class Generator(nn.Module):
    def __init__(self):
        super(Generator,self).__init__()
        self.layer1 = nn.Linear(100,7*7*256)
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                ('conv1', nn.ConvTranspose2d(256,128,3,2,1,1)),
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                ('conv3',nn.ConvTranspose2d(64,16,3,1,1)),
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                ('bn3',nn.BatchNorm2d(16)),
                ('conv4',nn.ConvTranspose2d(16,1,3,2,1,1)),
                ('relu4',nn.LeakyReLU())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Basic Concept

size 100인 Noise z에서
7*7*256 크기로 늘림

Autoencoder였으면 decoder 부분에 해당하는 generator

nn.Sequential 안에 layer 이름을 지정할 수 있게 OrderedDict를 사용함

형태에 관한 건 뒤에 DCGAN에서 추가적인 설명이 있음

```
class Generator(nn.Module):
    def __init__(self):
        super(Generator,self).__init__()
        self.layer1 = nn.Linear(100,7*7*256)
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,3,2,1,1)),
                ('relu1', nn.LeakyReLU()),
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                ('conv2', nn.ConvTranspose2d(128,64,3,1,1)),
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            ]))
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                ('conv3',nn.ConvTranspose2d(64,16,3,1,1)),
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                ('bn3',nn.BatchNorm2d(16)),
                ('conv4',nn.ConvTranspose2d(16,1,3,2,1,1)),
                ('relu4',nn.LeakyReLU())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Basic Concept

```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator,self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),   # batch x 16 x 28 x 28
                ('relu1',nn.LeakyReLU()),
                ('bn1',nn.BatchNorm2d(16)),
                ('conv2',nn.Conv2d(16,32,3,padding=1)),  # batch x 32 x 28 x 28
                ('relu2',nn.LeakyReLU()),
                ('bn2',nn.BatchNorm2d(32)),
                ('max1',nn.MaxPool2d(2,2))   # batch x 32 x 14 x 14
            ]))
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv3',nn.Conv2d(32,64,3,padding=1)),  # batch x 64 x 14 x 14
                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(64)),
                ('max2',nn.MaxPool2d(2,2)),
                ('conv4',nn.Conv2d(64,128,3,padding=1)),  # batch x 128 x 7 x 7
                ('relu4',nn.LeakyReLU())
            ]))
        self.fc = nn.Sequential(
                nn.Linear(128*7*7,1),
                nn.Sigmoid()
            )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size//num_gpus, -1)
        out = self.fc(out)
        return out
```

Basic Concept

Discriminator도 그냥 일반적인 형태.

```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator,self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),   # batch x 16 x 28 x 28
                ('relu1',nn.LeakyReLU()),
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                ('conv4',nn.Conv2d(64,128,3,padding=1)),  # batch x 128 x 7 x 7
                ('relu4',nn.LeakyReLU())
            ]))
        self.fc = nn.Sequential(
                nn.Linear(128*7*7,1),
                nn.Sigmoid()
            )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size//num_gpus, -1)
        out = self.fc(out)
        return out
```

Basic Concept

Discriminator도 그냥 일반적인 형태.

출력 값이 하나이고 0에서 1 값을 가지기 때문에 마지막에 sigmoid를 추가함

```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator,self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),   # batch x 16 x 28 x 28
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                ('max2',nn.MaxPool2d(2,2)),
                ('conv4',nn.Conv2d(64,128,3,padding=1)),  # batch x 128 x 7 x 7
                ('relu4',nn.LeakyReLU())
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        self.fc = nn.Sequential(
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            )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size//num_gpus, -1)
        out = self.fc(out)
        return out
```

Basic Concept

```
generator = nn.DataParallel(Generator()).cuda()
discriminator = nn.DataParallel(Discriminator()).cuda()

loss_func = nn.BCELoss()
gen_optim = torch.optim.Adam(generator.parameters(), lr=learning_rate)
dis_optim = torch.optim.Adam(discriminator.parameters(), lr=learning_rate)

ones_label = Variable(torch.ones(batch_size,1)).cuda()
zeros_label = Variable(torch.zeros(batch_size,1)).cuda()

# model restore

try:
    generator, discriminator = torch.load('./model/vanilla_gan.pkl')
    print("\n--------model restored--------\n")
except:
    print("\n--------model not restored--------\n")
    pass
```

Basic Concept

nn.DataParallel() 함수를 사용해 Multi-GPU에 모델을 올려서 학습

```
generator = nn.DataParallel(Generator()).cuda()
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각각 파라미터들을 따로 학습해야 하기 때문에 optimizer도 따로 만듦

```
generator = nn.DataParallel(Generator()).cuda()
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라벨로 사용할 0과 1값 생성

```
generator = nn.DataParallel(Generator()).cuda()
discriminator = nn.DataParallel(Discriminator()).cuda()

loss_func = nn.BCELoss()
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dis_optim = torch.optim.Adam(discriminator.parameters(), lr=learning_rate)

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각각 파라미터들을 따로 학습해야 하기 때문에 optimizer도 따로 만듦

라벨로 사용할 0과 1값 생성

학습된 모델 불러오는 부분

```
generator = nn.DataParallel(Generator()).cuda()
discriminator = nn.DataParallel(Discriminator()).cuda()

loss_func = nn.BCELoss()
gen_optim = torch.optim.Adam(generator.parameters(), lr=learning_rate)
dis_optim = torch.optim.Adam(discriminator.parameters(), lr=learning_rate)

ones_label = Variable(torch.ones(batch_size,1)).cuda()
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# model restore

try:
    generator, discriminator = torch.load('./model/vanilla_gan.pkl')
    print("\n--------model restored--------\n")
except:
    print("\n--------model not restored--------\n")
    pass
```

Basic Concept

```
# train

for i in range(epoch):
    for j,(image,label) in enumerate(train_loader):
        image = Variable(image).cuda()

        z = Variable(torch.rand(batch_size,100)).cuda()
        gen_optim.zero_grad()
        gen_fake = generator.forward(z)
        dis_fake = discriminator.forward(gen_fake)
        gen_loss = torch.sum(loss_func(dis_fake,ones_label))
        gen_loss.backward(retain_variables=True)
        gen_optim.step()

        dis_optim.zero_grad()
        dis_real = discriminator.forward(image)
        dis_loss = torch.sum(loss_func(dis_fake,zeros_label))+torch.sum(loss_func(dis_real,ones_label))
        dis_loss.backward()
        dis_optim.step()

    if i % 5 == 0:
        torch.save([generator,discriminator],'./model/vanilla_gan.pkl')

    print("{}th iteration gen_loss: {} dis_loss: {}".format(i,gen_loss.data,dis_loss.data))
    v_utils.save_image(gen_fake.data[0:20],"./gan_result/gen_{}.png".format(i), nrow=5)
```

Basic Concept

매번 새로운 noise를 생성해서 generate

```
# train

for i in range(epoch):
    for j,(image,label) in enumerate(train_loader):
        image = Variable(image).cuda()

        z = Variable(torch.rand(batch_size,100)).cuda()
        gen_optim.zero_grad()
        gen_fake = generator.forward(z)
        dis_fake = discriminator.forward(gen_fake)
        gen_loss = torch.sum(loss_func(dis_fake,ones_label))
        gen_loss.backward(retain_variables=True)
        gen_optim.step()

        dis_optim.zero_grad()
        dis_real = discriminator.forward(image)
        dis_loss = torch.sum(loss_func(dis_fake,zeros_label))+torch.sum(loss_func(dis_real,ones_label))
        dis_loss.backward()
        dis_optim.step()

    if i % 5 == 0:
        torch.save([generator,discriminator],'./model/vanilla_gan.pkl')

    print("{}th iteration gen_loss: {} dis_loss: {}".format(i,gen_loss.data,dis_loss.data))
    v_utils.save_image(gen_fake.data[0:20],"./gan_result/gen_{}.png".format(i), nrow=5)
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Basic Concept

매번 새로운 noise를 생성해서 generate

discriminator 통과해서 1과의 BCE loss 계산 및 업데이트

```
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for i in range(epoch):
    for j,(image,label) in enumerate(train_loader):
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```

Basic Concept

매번 새로운 noise를 생성해서 generate

discriminator 통과해서 1과의 BCE loss 계산 및 업데이트

실제 데이터와 가짜 데이터 가지고 discriminator 통과해서 이번엔 fake는 0, real은 1로 계산 및 업데이트

```
# train

for i in range(epoch):
    for j,(image,label) in enumerate(train_loader):
        image = Variable(image).cuda()

        z = Variable(torch.rand(batch_size,100)).cuda()
        gen_optim.zero_grad()
        gen_fake = generator.forward(z)
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        gen_loss = torch.sum(loss_func(dis_fake,ones_label))
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        dis_optim.step()

    if i % 5 == 0:
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    v_utils.save_image(gen_fake.data[0:20],"./gan_result/gen_{}.png".format(i), nrow=5)
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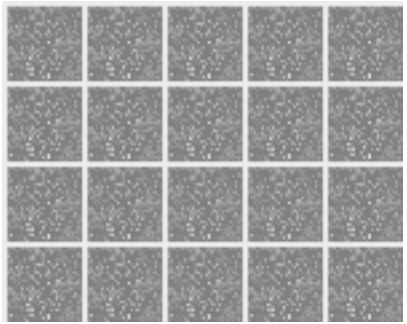
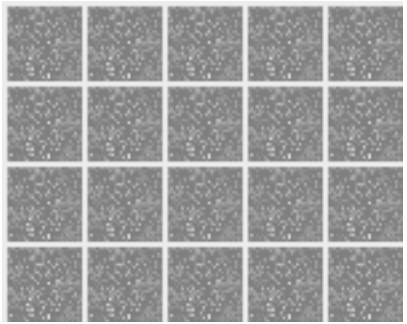
Basic Concept



Mode collapse

Oscillation

Basic Concept



Mode collapse

서로 다른 노이즈 값들로 generate 해도 하나의 mode로 수렴하는 현상

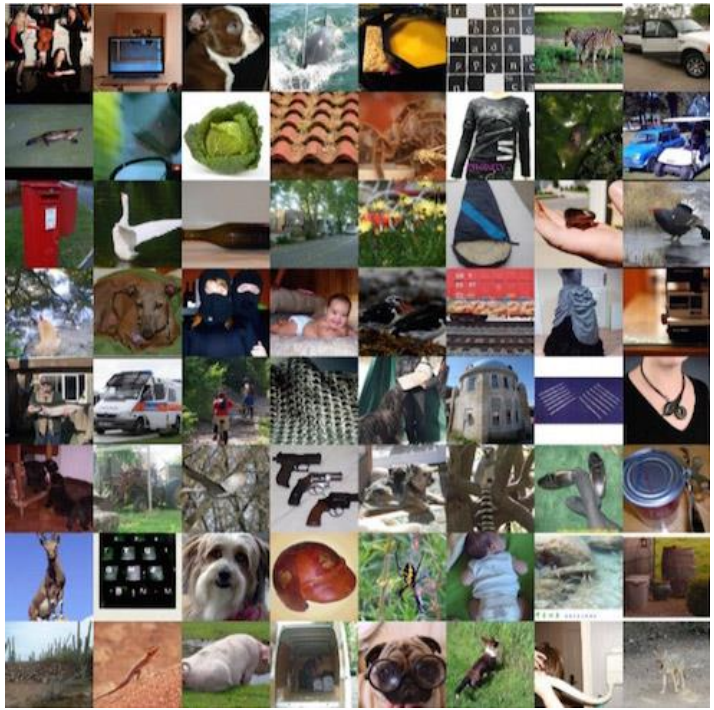
네트워크가 다양한 실제 이미지 같은 결과를 내기를 기대하는데 그럴 싸한 이미지만 만들어냄

Oscillation

GAN output들이 목표 카테고리가 여러 가지일 경우 왔다 갔다 하면서 다양한 결과값들을 만들어 내고 하나에 수렴하지 못하는 경우

Basic Concept

이러한 문제들이 있긴 하지만 잘될 땐 또 잘됨



Real Images

GAN Images

https://blog.openai.com/generative-models/

Basic Concept

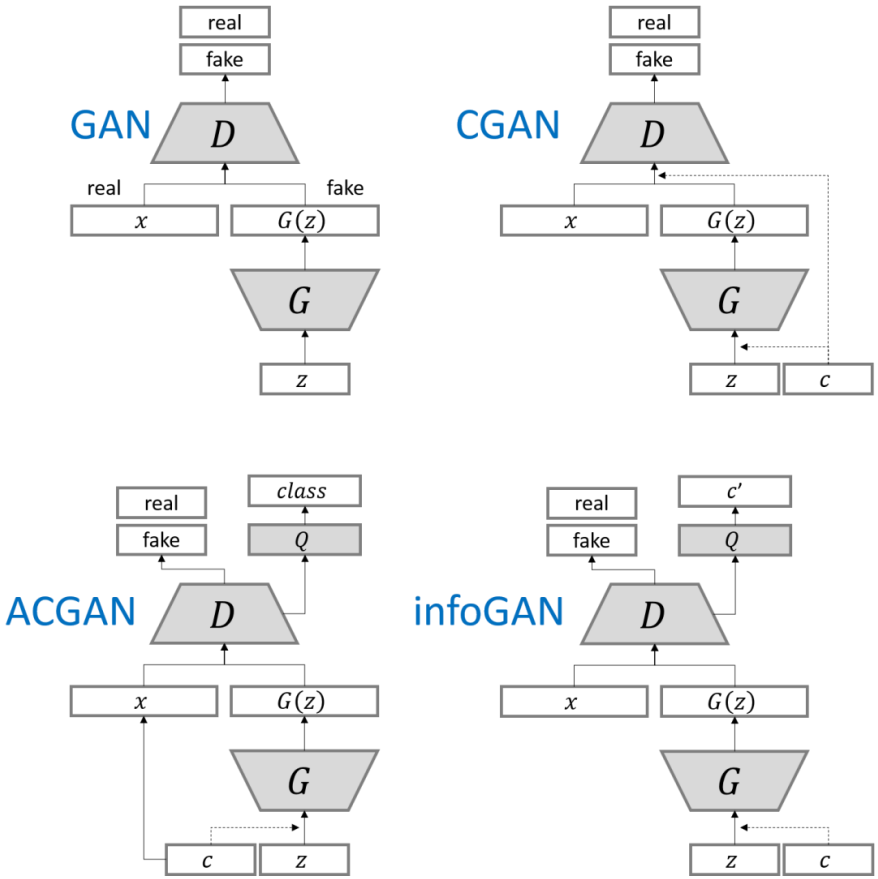
이러한 문제들이 있긴 하지만 잘될 땐 또 잘됨

VAE generated images

GAN Images

https://blog.openai.com/generative-models/

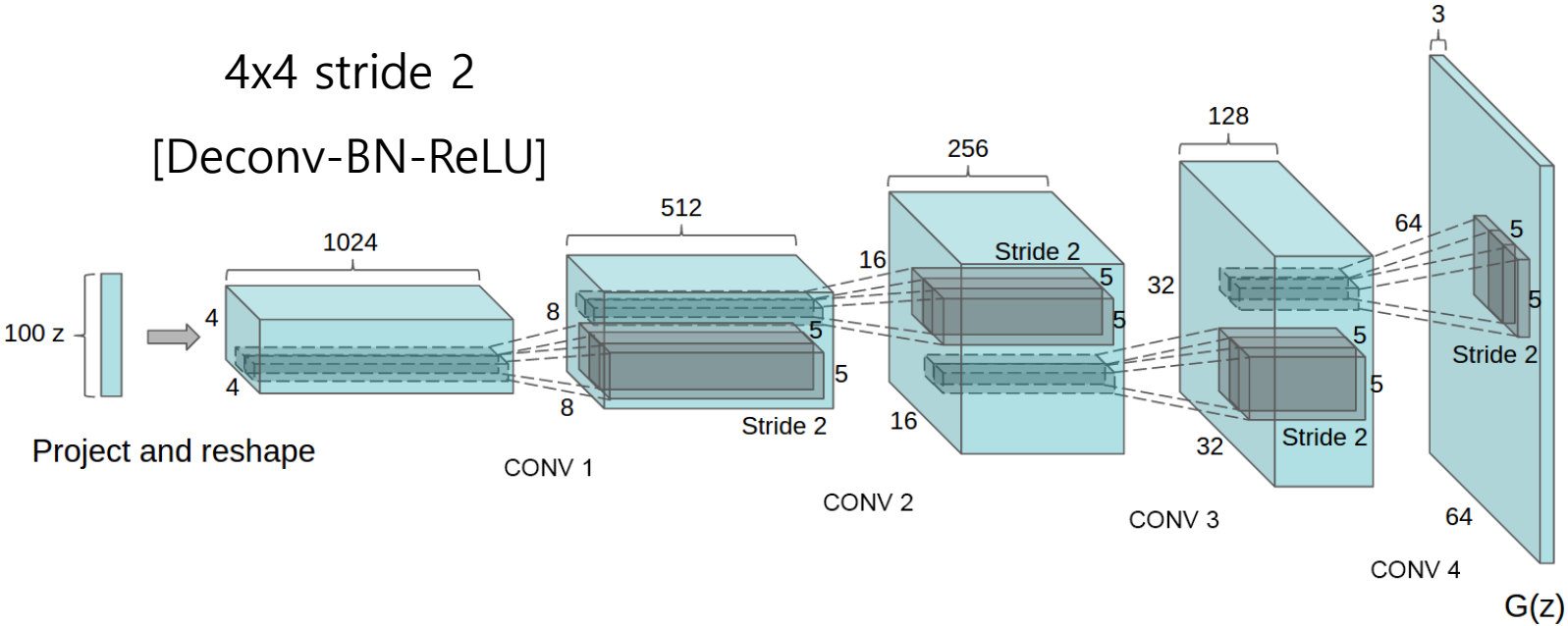
Models



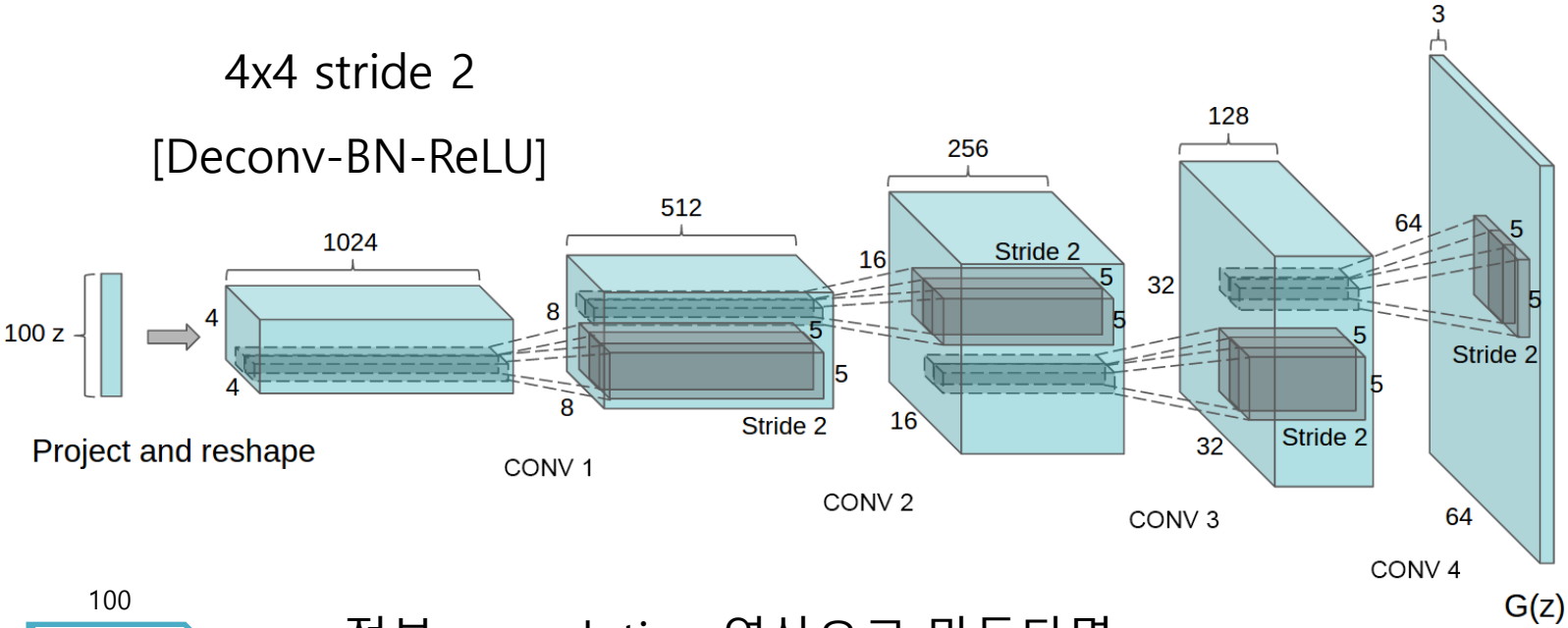
출처: https://github.com/hwalsuklee/tensorflow-generative-model-collections

Models

DCGAN



Models



100x1x1

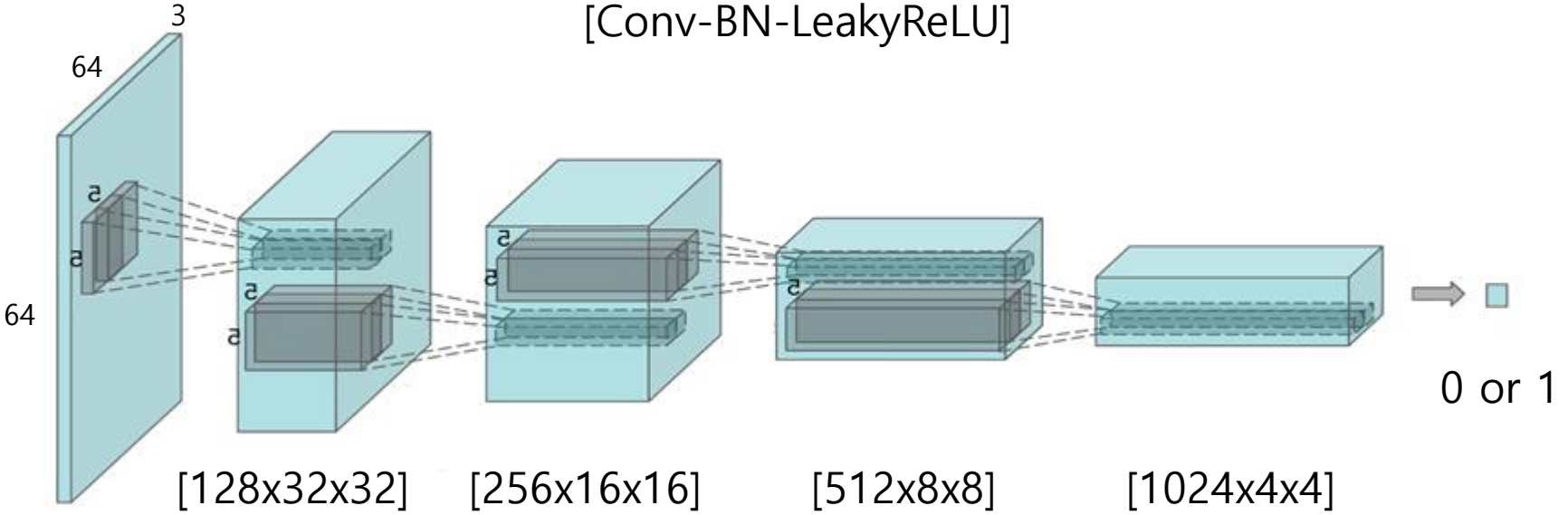
전부 convolution 연산으로 만든다면
z를 길이 100짜리 1차원 벡터가 아닌 [100,1,1]
3차원 벡터화시켜서 여기에 transposed convolution 적용

Models

DCGAN

4x4 stride 2

[Conv-BN-LeakyReLU]



Models

Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

- Pooling 제거하고 Strided Convolution으로 대체
- Batch Normalization 사용
- Fully Connected Layer 제거
- Generator에는 ReLU, 마지막단에만 Tanh
- Discriminator에는 LeakyReLU(0.2)

Models

1 epoch 결과

Models

DCGAN

5 epoch 결과

모델이 그냥 외운 것 아닌가?

Models

모델이 그냥 외운 것 아닌가?

확인을 어떻게 하지?

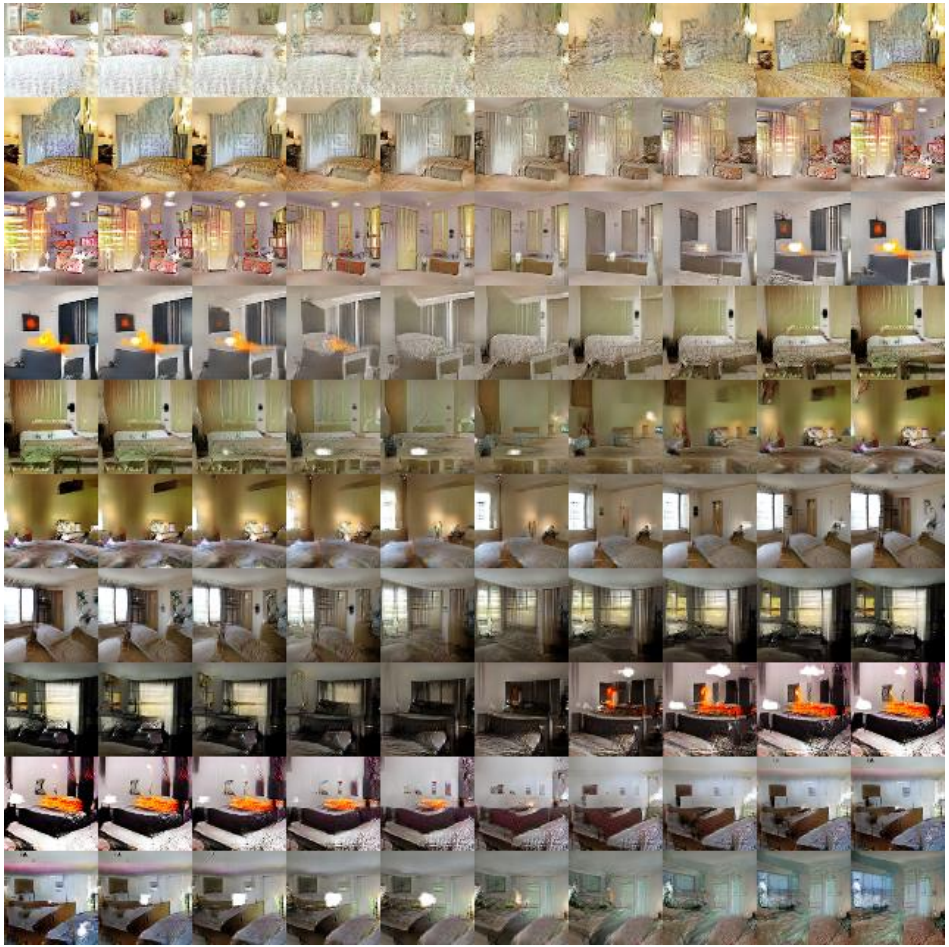
모델이 그냥 외운 것 아닌가?

확인을 어떻게 하지?

z를 interpolation하면서 어떻게 변하나 확인해보자
만약에 급격하게 확 변하면 외운 것이고 아니면 어떤 의미를 이해한 것으로 판단할 수 있다!

Models

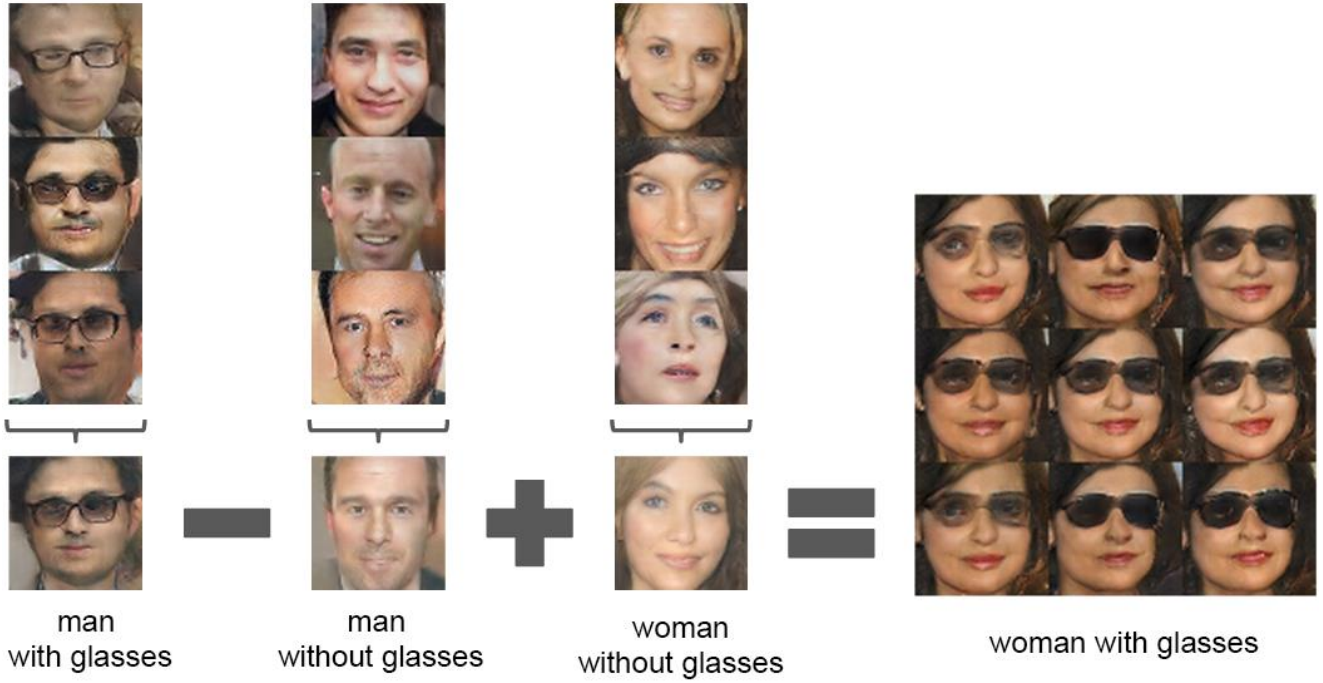
DCGAN



없던 창문이 생겨남

TV가 창문으로 변함

Models



Vector Arithmetic이 가능하다!

Models

이런 Interpolation도 가능하다!

Models

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

출처: https://github.com/hwalsuklee/tensorflow-generative-model-collections

Models

CGAN

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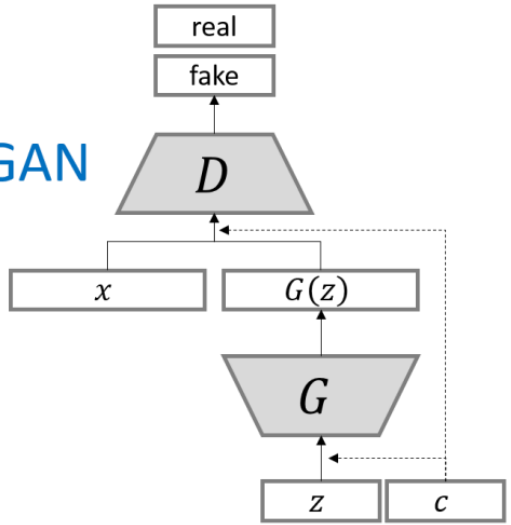
CGAN



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Models

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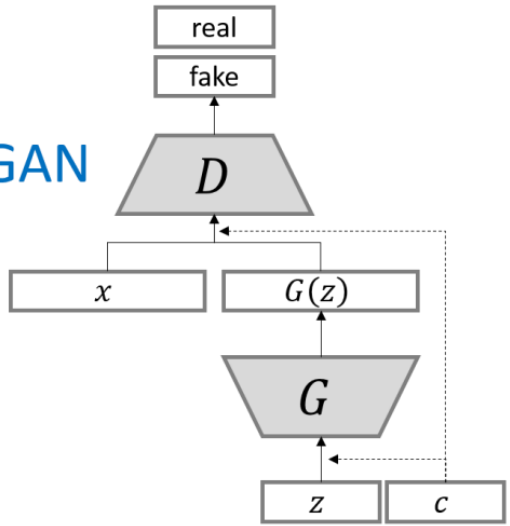
y가 label

CGAN



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Models

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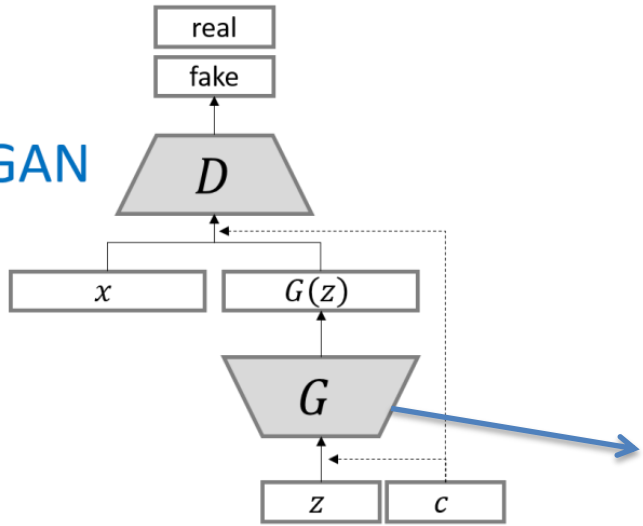

이미지를 생성할 때 class 라벨을 z와 함께 전달

출처: https://github.com/hwalsuklee/tensorflow-generative-model-collections

Models

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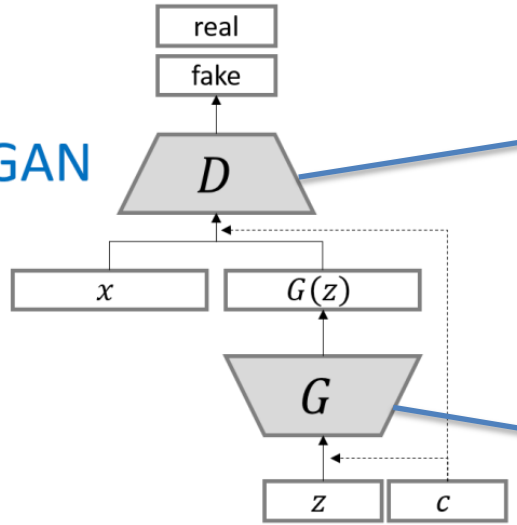
CGAN



Discriminator 에도class 라벨을 z와 함께 전달

이미지를 생성할 때 class 라벨을 z와 함께 전달

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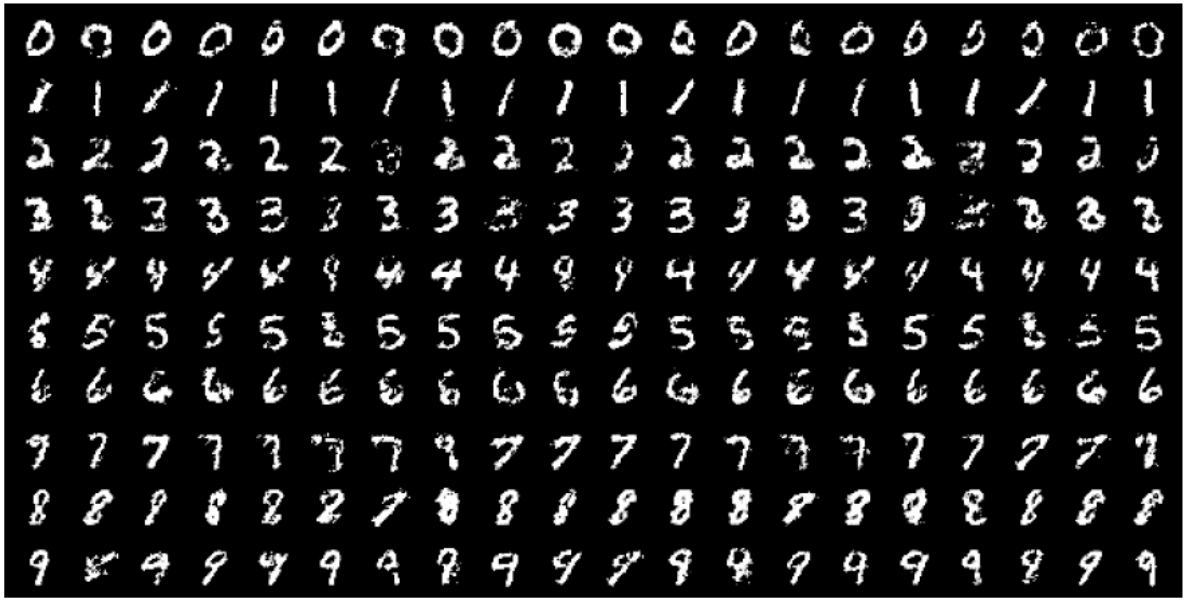

Figure 2: Generated MNIST digits, each row conditioned on one label

Models

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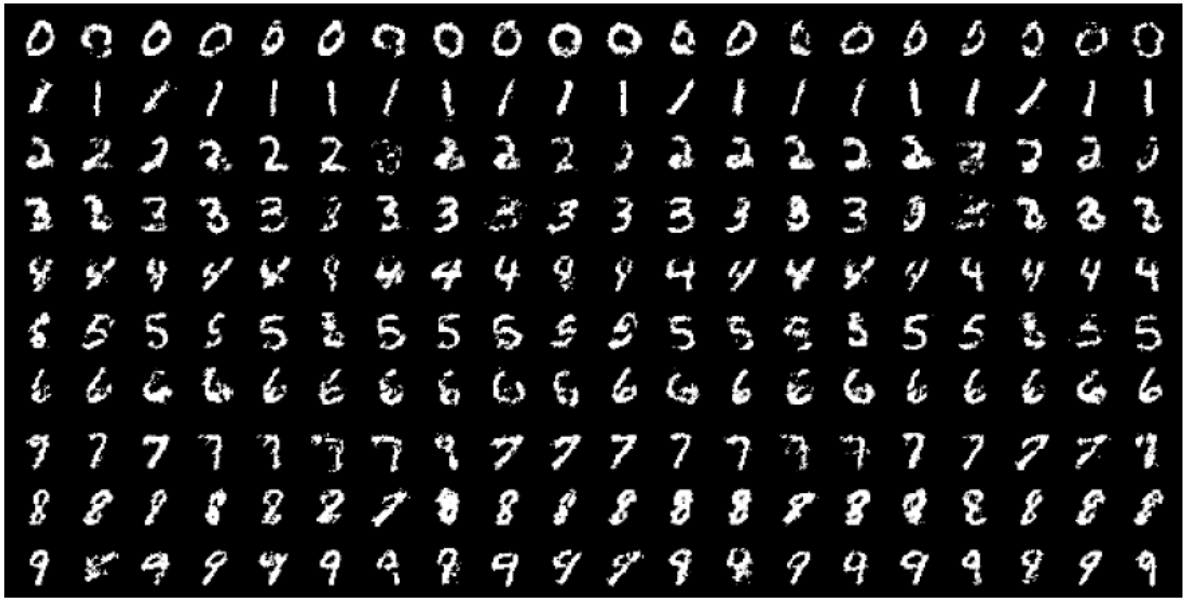
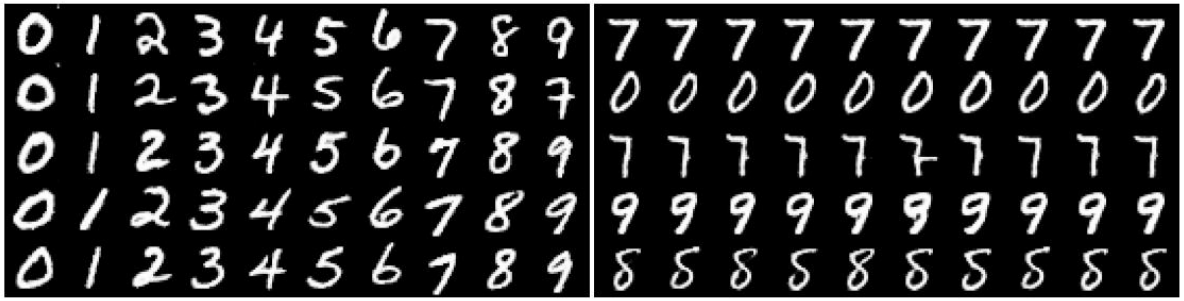


Figure 2: Generated MNIST digits, each row conditioned on one label

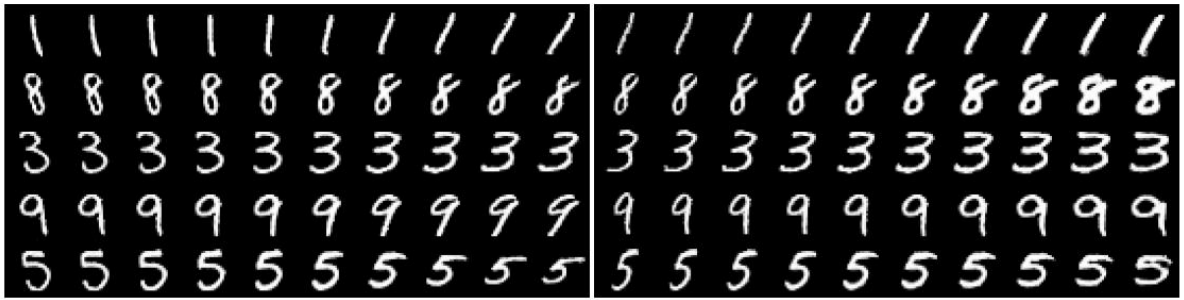
꼭 label이 있어야 가능한 건가?

Models



(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)

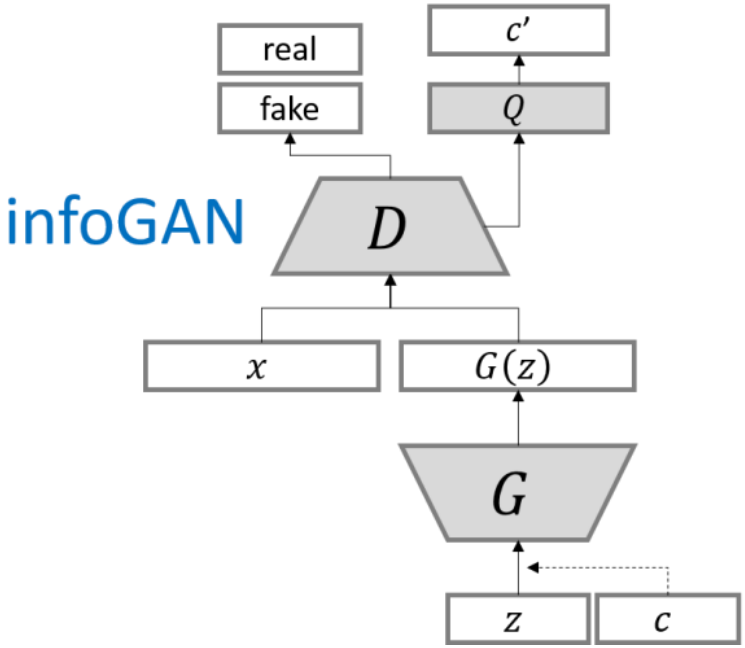


(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

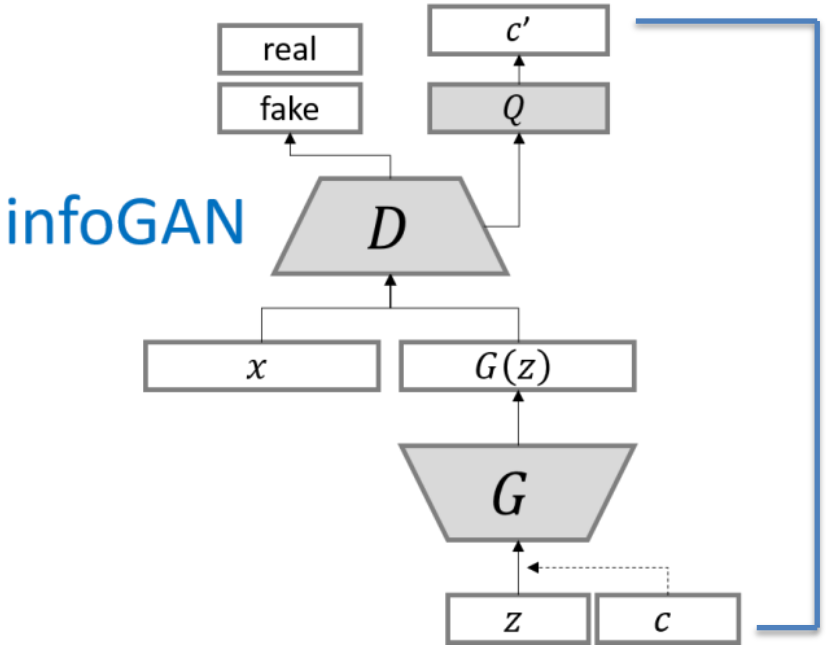
(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

Unsupervised Learning으로 카테고리나 기울어진 정도, 두께를 찾을 수 있다!

Models



Models

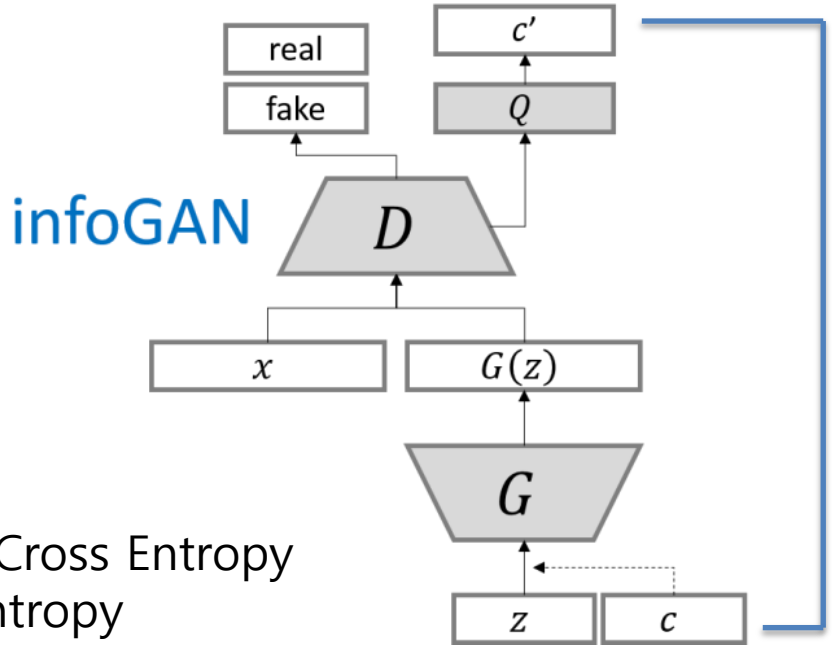


기존의 GAN

+

Generator에 넣은 c가
Discriminator를 통과
-해도 남아있게 만들자

Models



기존의 GAN

+

Generator에 넣은 c가
Discriminator를 통과
-해도 남아있게 만들자

Real Fake는 Binary Cross Entropy
discrete 은 Cross Entropy
continuous는 MSE

Models

$$\min_G \max_D V_I(D, G) = V(D, G) - \lambda I\ (c; G(z, c))$$

Models

Mutual Information
이 값이 클수록 관련도가 높음

$$\min_{G} \max_{D} V_I(D, G) = V(D, G) - \lambda I\ (c; G(z, c))$$

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원래는 이 식인데 직접 구하기 힘들기 때문에 Variational Mutual Information Maximization이란 방법을 사용함

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VAE에서처럼 P를 근사하는 Q를 만들어서 둘의 차이를 줄이는 방법

Models

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VAE에서처럼 P를 근사하는 Q를 만들어서 둘의 차이를 줄이는 방법

$$\min_{G,Q} \max_D V_{InfoGAN}(D,G,Q) = V(D,G) - \lambda L_1(G,Q)$$

Models

Mutual Information
이 값이 클수록 관련도가 높음

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I\ (c; G(z,c))$$

원래는 이 식인데 직접 구하기 힘들기 때문에 Variational Mutual Information Maximization이란 방법을 사용함

VAE에서처럼 P를 근사하는 Q를 만들어서 둘의 차이를 줄이는 방법

기존 GAN loss

$$\min_{G,Q} \max_D V_{InfoGAN}(D,G,Q) = V(D,G) - \lambda L_1(G,Q)$$

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Models

Mutual Information
이 값이 클수록 관련도가 높음

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I\ (c; G(z,c))$$

원래는 이 식인데 직접 구하기 힘들기 때문에 Variational Mutual Information Maximization이란 방법을 사용함

VAE에서처럼 P를 근사하는 Q를 만들어서 둘의 차이를 줄이는 방법

기존 GAN loss Mutual Information

$$\min_{G,Q} \max_D V_{InfoGAN}(D,G,Q) = V(D,G) - \lambda L_1(G,Q)$$

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Mutual Information의
Variational Lowerbound

Models

```python
def int_to_onehot(z_label):
    one_hot_array = np.zeros(shape=[len(z_label), discrete_latent_size])
    one_hot_array[np.arange(len(z_label)), z_label] = 1
    return one_hot_array


class Generator(nn.Module):
    def __init__(self):
        super(Generator,self).__init__()
        self.layer1 = nn.Sequential(
                    nn.Linear(110,1024),
                    nn.BatchNorm1d(1024),
                    nn.ReLU(),
                    nn.Linear(1024,7*7*256),
                    nn.BatchNorm1d(7*7*256),
                    nn.ReLU(),
            )
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,1,1)), # [batch,256,7,7] -> [batch,128,14,14]
                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,31)),    # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
                ('relu2', nn.LeakyReLU()),

            ]))
        self.layer3 = nn.Sequential(OrderedDict([
                ('conv3',nn.ConvTranspose2d(64,32,3,1),      # [batch,64,14,14] -> [batch,16,14,14]
                ('bn3',nn.BatchNorm2d(32)),
                ('relu3',nn.LeakyReLU()),
                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),     # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models

라벨이 들어오면
one-hot vector화

```python
def int_to_onehot(z_label):
    one_hot_array = np.zeros(shape=[len(z_label), discrete_latent_size])
    one_hot_array[np.arange(len(z_label)), z_label] = 1
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                    nn.ReLU(),
                    nn.Linear(1024,7*7*256),
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                    nn.ReLU(),
                )
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,1,1)), # [batch,256,7,7] -> [batch,128,14,14]
                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,31)),    # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
                ('relu2', nn.LeakyReLU()),

            ]))
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                ('bn3',nn.BatchNorm2d(32)),
                ('relu3',nn.LeakyReLU()),
                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),     # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models

라벨이 들어오면
one-hot vector화

z(100) + category(10)
에서 256x7x7 벡터화

```python
def int_to_onehot(z_label):
    one_hot_array = np.zeros(shape=[len(z_label), discrete_latent_size])
    one_hot_array[np.arange(len(z_label)), z_label] = 1
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class Generator(nn.Module):
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        self.layer1 = nn.Sequential(
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                    nn.BatchNorm1d(1024),
                    nn.ReLU(),
                    nn.Linear(1024,7*7*256),
                    nn.BatchNorm1d(7*7*256),
                    nn.ReLU(),
                )
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,1,1)), # [batch,256,7,7] -> [batch,128,14,14]
                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,31)),    # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
                ('relu2', nn.LeakyReLU()),

            ]))
        self.layer3 = nn.Sequential(OrderedDict([
                ('conv3',nn.ConvTranspose2d(64,32,3,1),      # [batch,64,14,14] -> [batch,16,14,14]
                ('bn3',nn.BatchNorm2d(32)),
                ('relu3',nn.LeakyReLU()),
                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),     # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models

라벨이 들어오면
one-hot vector화

z(100) + category(10)
에서 256x7x7 벡터화

Conv Transpose,
Batch Norm
Leaky ReLU

```python
def int_to_onehot(z_label):
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                    nn.BatchNorm1d(7*7*256),
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                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,3,1,1)),  # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
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                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),      # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models

라벨이 들어오면
one-hot vector화

z(100) + category(10)
에서 256x7x7 벡터화

Conv Transpose,
Batch Norm
Leaky ReLU

마지막에만 Tanh
-1~1로 맞춰주려고

```python
def int_to_onehot(z_label):
    one_hot_array = np.zeros(shape=[len(z_label), discrete_latent_size])
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                    nn.ReLU(),
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                    nn.ReLU(),
                )
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                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,31)),    # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
                ('relu2', nn.LeakyReLU()),

            ]))
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                ('conv3',nn.ConvTranspose2d(64,32,3,1),      # [batch,64,14,14] -> [batch,16,14,14]
                ('bn3',nn.BatchNorm2d(32)),
                ('relu3',nn.LeakyReLU()),
                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),     # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models

라벨이 들어오면
one-hot vector화

z(100) + category(10)
에서 256x7x7 벡터화

Conv Transpose,
Batch Norm
Leaky ReLU

마지막에만 Tanh
-1~1로 맞춰주려고

forward 함수,
batch_size/num_gpus는
각 gpu에 분산처리하기 위함

```python
def int_to_onehot(z_label):
    one_hot_array = np.zeros(shape=[len(z_label), discrete_latent_size])
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                    nn.Linear(110,1024),
                    nn.BatchNorm1d(1024),
                    nn.ReLU(),
                    nn.Linear(1024,7*7*256),
                    nn.BatchNorm1d(7*7*256),
                    nn.ReLU(),
                )
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv1', nn.ConvTranspose2d(256,128,1,1)),  # [batch,256,7,7] -> [batch,128,14,14]
                ('bn1', nn.BatchNorm2d(128)),
                ('relu1', nn.LeakyReLU()),
                ('conv2', nn.ConvTranspose2d(128,64,31)),    # [batch,128,14,14] -> [batch,64,14,14]
                ('bn2', nn.BatchNorm2d(64)),
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            ]))
        self.layer3 = nn.Sequential(OrderedDict([
                ('conv3',nn.ConvTranspose2d(64,32,3,1),      # [batch,64,14,14] -> [batch,16,14,14]
                ('bn3',nn.BatchNorm2d(32)),
                ('relu3',nn.LeakyReLU()),
                ('conv4',nn.ConvTranspose2d(32,1,3,2,)),     # [batch,16,14,14] -> [batch,1,28,28]
                ('tanh',nn.Tanh())
            ]))

    def forward(self,z):
        out = self.layer1(z)
        out = out.view(batch_size//num_gpus,256,7,7)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Models


```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator,self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),            # [batch,1,28,28] -> [batch,16,28,28]
                ('relu1',nn.LeakyReLU()),
                ('conv2',nn.Conv2d(16,32,3,stride=2,padding=1)),  # [batch,16,28,28] -> [batch,32,28,28]
                ('bn2',nn.BatchNorm2d(32)),
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            ]))
        self.layer2 = nn.Sequential(OrderedDict([
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                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)), # [batch,64,7,7] -> [batch,128,7,7]
                ('bn4',nn.BatchNorm2d(128)),
                ('relu4',nn.LeakyReLU())
            ]))
        self.fc = nn.Sequential(
                nn.Linear(128*7*7,1),
                nn.Sigmoid()
            )
        self.fc2 = nn.Sequential(
                nn.Linear(128*7*7,10),
                nn.LeakyReLU(),
            )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size//num_gpus, -1)
        output = self.fc(out)
        label = self.fc2(out)
        return output,label
```

Models

DCGAN 구조를 따라서
Conv->BatchNorm->LeakyReLU

```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator.self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),                  # [batch,1,28,28] -> [batch,16,28,28]
                ('relu1',nn.LeakyReLU()),
                ('conv2',nn.Conv2d(16,32,3,stride=2,padding=1)),        # [batch,16,28,28] -> [batch,32,28,28]
                ('bn2',nn.BatchNorm2d(32)),
                ('relu2',nn.LeakyReLU()),

            ]))
        self.layer2 = nn.Sequential(OrderedDict([
                ('conv3',nn.Conv2d(32,64,3,padding=1)),                 # [batch,32,14,14] -> [batch,64,14,14]
                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)),       # [batch,64,7,7] -> [batch,128,7,7]
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        self.fc = nn.Sequential(
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                nn.LeakyReLU(),
            )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size//num_gpus, -1)
        output = self.fc(out)
        label = self.fc2(out)
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```

Models

DCGAN 구조를 따라서
Conv->BatchNorm->LeakyReLU

Conv->BatchNorm->LeakyReLU

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                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)),       # [batch,64,7,7] -> [batch,128,7,7]
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            ]))
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```

Models

DCGAN 구조를 따라서
Conv->BatchNorm->LeakyReLU

Conv->BatchNorm->LeakyReLU

GAN output 구하는 부분
라벨이 0 or 1 이기 때문에
마지막 단에 sigmoid

```python
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator.self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
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                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)),       # [batch,64,7,7] -> [batch,128,7,7]
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        out = out.view(batch_size//num_gpus, -1)
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```

Models

DCGAN 구조를 따라서
Conv->BatchNorm->LeakyReLU

Conv->BatchNorm->LeakyReLU

GAN output 구하는 부분
라벨이 0 or 1 이기 때문에
마지막 단에 sigmoid

Categorical vector를 구하는 부분

```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator.self).__init__()
        self.layer1 = nn.Sequential(OrderedDict([
                ('conv1',nn.Conv2d(1,16,3,padding=1)),                  # [batch,1,28,28] -> [batch,16,28,28]
                ('relu1',nn.LeakyReLU()),
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                ('relu3',nn.LeakyReLU()),
                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)),       # [batch,64,7,7] -> [batch,128,7,7]
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            ]))
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            )
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            )

    def forward(self,x):
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        out = out.view(batch_size//num_gpus, -1)
        output = self.fc(out)
        label = self.fc2(out)
        return output,label
```

Models

DCGAN 구조를 따라서
Conv->BatchNorm->LeakyReLU

Conv->BatchNorm->LeakyReLU

GAN output 구하는 부분
라벨이 0 or 1 이기 때문에
마지막 단에 sigmoid

Categorical vector를 구하는 부분

forward 함수,
batch_size/num_gpus는
각 gpu에 분산처리하기 위함

```
class Discriminator(nn.Module):
    def __init__(self):
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                ('bn3',nn.BatchNorm2d(64)),
                ('conv4',nn.Conv2d(64,128,3,stride=2,padding=1)),       # [batch,64,7,7] -> [batch,128,7,7]
                ('bn4',nn.BatchNorm2d(128)),
                ('relu4',nn.LeakyReLU())
            ]))
        self.fc = nn.Sequential(
                nn.Linear(128*7*7,1),
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            )
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    def forward(self,x):
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```

Models


```
# put class instance on multi gpu

generator = nn.DataParallel(Generator(),device_ids=[0])
discriminator = nn.DataParallel(Discriminator(),device_ids=[0])

# put labels on multi gpu

ones_label = Variable(torch.ones(batch_size,1)).cuda()
zeros_label = Variable(torch.zeros(batch_size,1)).cuda()

gan_loss_func = nn.BCELoss()
cat_loss_func = nn.CrossEntropyLoss()

gen_optim = torch.optim.Adam(generator.parameters(), lr=learning_rate,betas=(0.5,0.999))
dis_optim = torch.optim.Adam(discriminator.parameters(), lr=learning_rate,betas=(0.5,0.999))


try:
    generator, discriminator = torch.load('./model/infogan.pkl')
    print("\n--------model restored--------\n")
except:
    print("\n--------model not restored--------\n")
    pass
```

Models

nn.DataParallel() 함수를 통해 인스턴스를 multi gpu에 올릴 수 있음

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# put class instance on multi gpu

generator = nn.DataParallel(Generator(),device_ids=[0])
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Models

nn.DataParallel() 함수를 통해 인스턴스를 multi gpu에 올릴 수 있음

GAN Label

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zeros_label = Variable(torch.zeros(batch_size,1)).cuda()

gan_loss_func = nn.BCELoss()
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```

Models

nn.DataParallel() 함수를 통해 인스턴스를 multi gpu에 올릴 수 있음

GAN Label

각각 상황에 맞는 Loss Function

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try:
    generator, discriminator = torch.load('./model/infogan.pkl')
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except:
    print("\n--------model not restored--------\n")
    pass
```

Models

nn.DataParallel() 함수를 통해 인스턴스를 multi gpu에 올릴 수 있음

GAN Label

각각 상황에 맞는 Loss Function

optimizer

```
# put class instance on multi gpu

generator = nn.DataParallel(Generator(),device_ids=[0])
discriminator = nn.DataParallel(Discriminator(),device_ids=[0])

# put labels on multi gpu

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Models

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discriminator = nn.DataParallel(Discriminator(),device_ids=[0])
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GAN Label

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각각 상황에 맞는 Loss Function

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cat_loss_func = nn.CrossEntropyLoss()
```

optimizer

```
gen_optim = torch.optim.Adam(generator.parameters(), lr=learning_rate,betas=(0.5,0.999))
dis_optim = torch.optim.Adam(discriminator.parameters(), lr=learning_rate,betas=(0.5,0.999))
```

모델 저장

```
try:
    generator, discriminator = torch.load('./model/infogan.pkl')
    print("\n--------model restored--------\n")
except:
    print("\n--------model not restored--------\n")
    pass
```

Models

```
for i in range(epoch):
    for j,(image,_) in enumerate(train_loader):

        # put image & label on gpu
        image = Variable(image).cuda()

        # generator
        for k in range(2):
            z_random = np.random.rand(batch_size,100)
            z_label = np.random.randint(0, 10, size=batch_size)

            # change first 10 labels from random to 0~9
            for l in range(10):
                z_label[l]=l

            # preprocess z
            z_variable = Variable(torch.from_numpy(z_label)).cuda()
            z_label_onehot = int_to_onehot(z_label)
            z_concat = np.concatenate([z_random, z_label_onehot], axis=1)
            z = Variable(torch.from_numpy(z_concat).type_as(torch.FloatTensor())).cuda()
            z_label_onehot = Variable(torch.from_numpy(z_label_onehot).type_as(torch.FloatTensor())).cuda()

            # calculate loss and apply gradients
            # gen_loss = gan loss(fake) + categorical loss
            gen_optim.zero_grad()
            gen_fake = generator.forward(z)
            dis_fake,label_fake = discriminator.forward(gen_fake)
            gen_loss = torch.sum(gan_loss_func(dis_fake,ones_label)) \
                     + torch.sum(cat_loss_func(label_fake,z_variable))

            gen_loss.backward(retain_graph=True)
            gen_optim.step()

        # discriminator
        # dis_loss = gan_loss(fake & real) + categorical loss
        dis_optim.zero_grad()
        dis_real, label_real = discriminator.forward(image)
        dis_loss = torch.sum(gan_loss_func(dis_fake,zeros_label))\
                 + torch.sum(gan_loss_func(dis_real,ones_label))
                 #+ discrete_latent_size * torch.sum(loss_func(label_real,z_label_onehot))

        dis_loss.backward()
        dis_optim.step()
```

Models

Noise z, category variable을 합쳐서 전달 및 비교할 수 있게 세팅하는 단계

```
for i in range(epoch):
    for j,(image,_) in enumerate(train_loader):

        # put image & label on gpu
        image = Variable(image).cuda()

        # generator
        for k in range(2):
            z_random = np.random.rand(batch_size,100)
            z_label = np.random.randint(0, 10, size=batch_size)

            # change first 10 labels from random to 0~9
            for l in range(10):
                z_label[l]=l

            # preprocess z
            z_variable = Variable(torch.from_numpy(z_label)).cuda()
            z_label_onehot = int_to_onehot(z_label)
            z_concat = np.concatenate([z_random, z_label_onehot], axis=1)
            z = Variable(torch.from_numpy(z_concat).type_as(torch.FloatTensor())).cuda()
            z_label_onehot = Variable(torch.from_numpy(z_label_onehot).type_as(torch.FloatTensor())).cuda()

            # calculate loss and apply gradients
            # gen_loss = gan loss(fake) + categorical loss
            gen_optim.zero_grad()
            gen_fake = generator.forward(z)
            dis_fake,label_fake = discriminator.forward(gen_fake)
            gen_loss = torch.sum(gan_loss_func(dis_fake,ones_label)) \
                     + torch.sum(cat_loss_func(label_fake,z_variable))

            gen_loss.backward(retain_graph=True)
            gen_optim.step()

        # discriminator
        # dis_loss = gan_loss(fake & real) + categorical loss
        dis_optim.zero_grad()
        dis_real, label_real = discriminator.forward(image)
        dis_loss = torch.sum(gan_loss_func(dis_fake,zeros_label))\
                 + torch.sum(gan_loss_func(dis_real,ones_label))
                 #+ discrete_latent_size * torch.sum(loss_func(label_real,z_label_onehot))

        dis_loss.backward()
        dis_optim.step()
```

Models

Noise z, category variable을 합쳐서 전달 및 비교할 수 있게 세팅하는 단계

Generator 학습
gan loss + category loss

retain graph는 generator 연산 값들이 discriminator에 필요하기 때문에 release 안 하기 위함

```
for i in range(epoch):
    for j,(image,_) in enumerate(train_loader):

        # put image & label on gpu
        image = Variable(image).cuda()

        # generator
        for k in range(2):
            z_random = np.random.rand(batch_size,100)
            z_label = np.random.randint(0, 10, size=batch_size)

            # change first 10 labels from random to 0~9
            for l in range(10):
                z_label[l]=l

            # preprocess z
            z_variable = Variable(torch.from_numpy(z_label)).cuda()
            z_label_onehot = int_to_onehot(z_label)
            z_concat = np.concatenate([z_random, z_label_onehot], axis=1)
            z = Variable(torch.from_numpy(z_concat).type_as(torch.FloatTensor())).cuda()
            z_label_onehot = Variable(torch.from_numpy(z_label_onehot).type_as(torch.FloatTensor())).cuda()

            # calculate loss and apply gradients
            # gen_loss = gan loss(fake) + categorical loss
            gen_optim.zero_grad()
            gen_fake = generator.forward(z)
            dis_fake,label_fake = discriminator.forward(gen_fake)
            gen_loss = torch.sum(gan_loss_func(dis_fake,ones_label)) \
                     + torch.sum(cat_loss_func(label_fake,z_variable))

            gen_loss.backward(retain_graph=True)
            gen_optim.step()

        # discriminator
        # dis_loss = gan_loss(fake & real) + categorical loss
        dis_optim.zero_grad()
        dis_real, label_real = discriminator.forward(image)
        dis_loss = torch.sum(gan_loss_func(dis_fake,zeros_label))\
                 + torch.sum(gan_loss_func(dis_real,ones_label))
                 #+ discrete_latent_size * torch.sum(loss_func(label_real,z_label_onehot))

        dis_loss.backward()
        dis_optim.step()
```

Models

Noise z, category variable을 합쳐서 전달 및 비교할 수 있게 세팅하는 단계

Generator 학습
gan loss + category loss

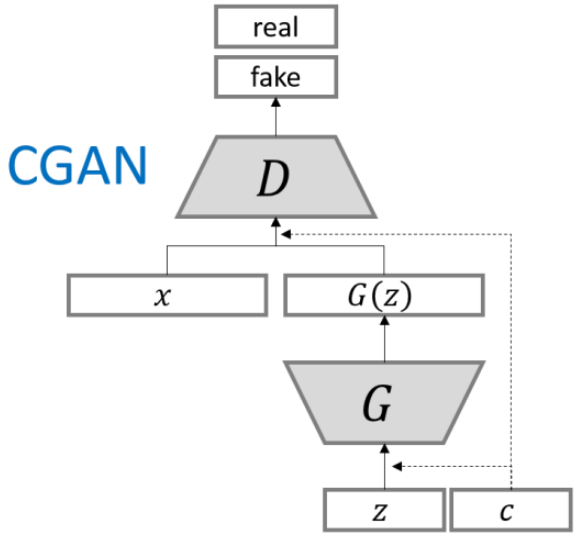
retain graph는 generator 연산 값들이 discriminator에 필요하기 때문에 release 안 하기 위함

Discriminator 학습
gan loss만 있음

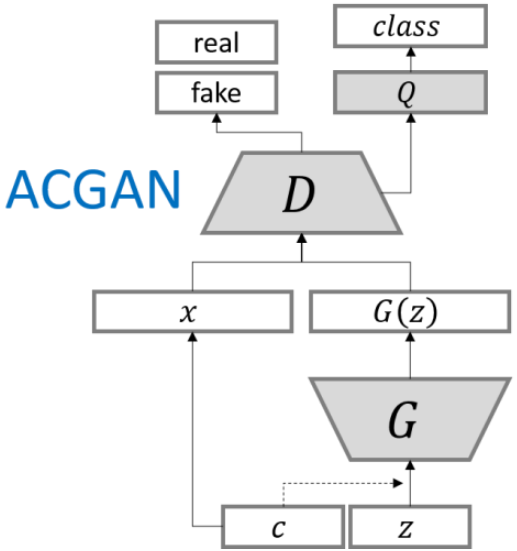
실제 라벨도 사용하면 semi-supervised learning(?)

```
for i in range(epoch):
    for j,(image,_) in enumerate(train_loader):

        # put image & label on gpu
        image = Variable(image).cuda()

        # generator
        for k in range(2):
            z_random = np.random.rand(batch_size,100)
            z_label = np.random.randint(0, 10, size=batch_size)

            # change first 10 labels from random to 0~9
            for l in range(10):
                z_label[l]=l

            # preprocess z
            z_variable = Variable(torch.from_numpy(z_label)).cuda()
            z_label_onehot = int_to_onehot(z_label)
            z_concat = np.concatenate([z_random, z_label_onehot], axis=1)
            z = Variable(torch.from_numpy(z_concat).type_as(torch.FloatTensor())).cuda()
            z_label_onehot = Variable(torch.from_numpy(z_label_onehot).type_as(torch.FloatTensor())).cuda()

            # calculate loss and apply gradients
            # gen_loss = gan loss(fake) + categorical loss
            gen_optim.zero_grad()
            gen_fake = generator.forward(z)
            dis_fake,label_fake = discriminator.forward(gen_fake)
            gen_loss = torch.sum(gan_loss_func(dis_fake,ones_label)) \
                     + torch.sum(cat_loss_func(label_fake,z_variable))

            gen_loss.backward(retain_graph=True)
            gen_optim.step()

        # discriminator
        # dis_loss = gan_loss(fake & real) + categorical loss
        dis_optim.zero_grad()
        dis_real, label_real = discriminator.forward(image)
        dis_loss = torch.sum(gan_loss_func(dis_fake,zeros_label))\
                 + torch.sum(gan_loss_func(dis_real,ones_label))
                 #+ discrete_latent_size * torch.sum(loss_func(label_real,z_label_onehot))

        dis_loss.backward()
        dis_optim.step()
```

Models



CGAN은 생성 및 구분 시 label을
추가 정보로만 제공했다면



ACGAN은 Auxiliary Classifier를
추가하여 클래스를 구분하게 만듦

Models

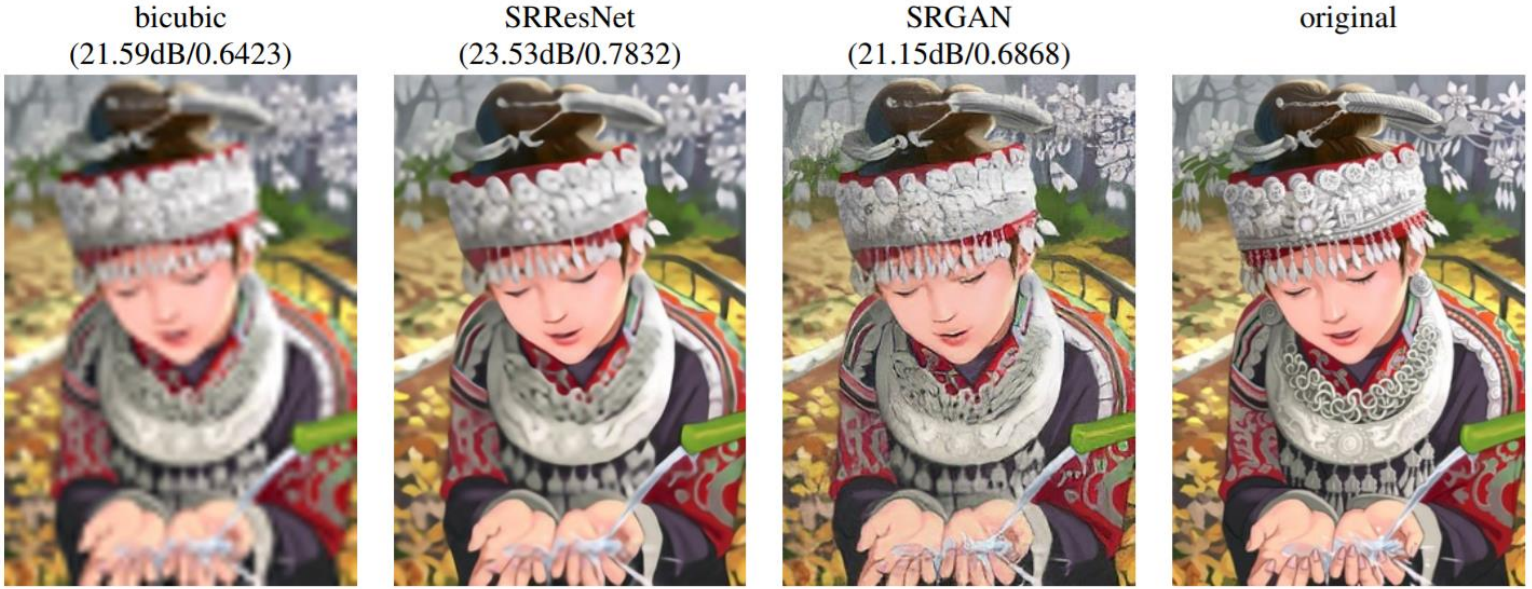
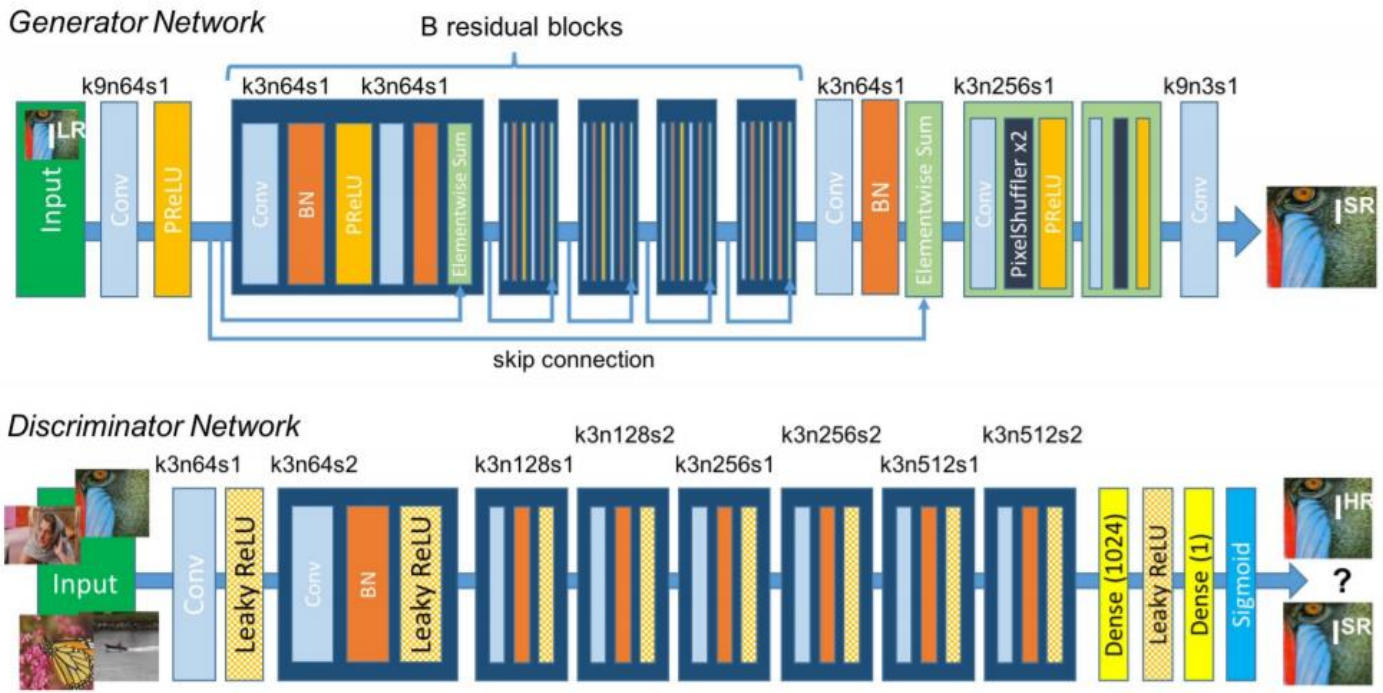


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]

Models

SRGAN

저해상도

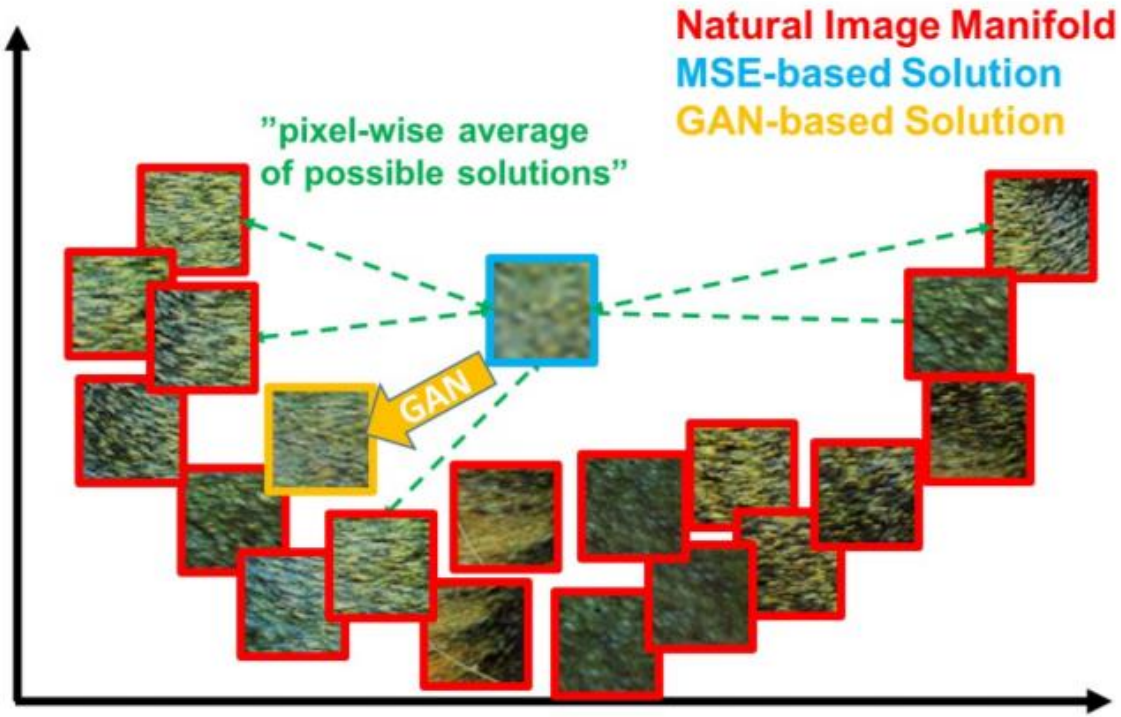


고해상도

Real

Fake

Models



Mode collapse가 일어나는 GAN의 특성이 오히려 장점이 된 케이스

Models

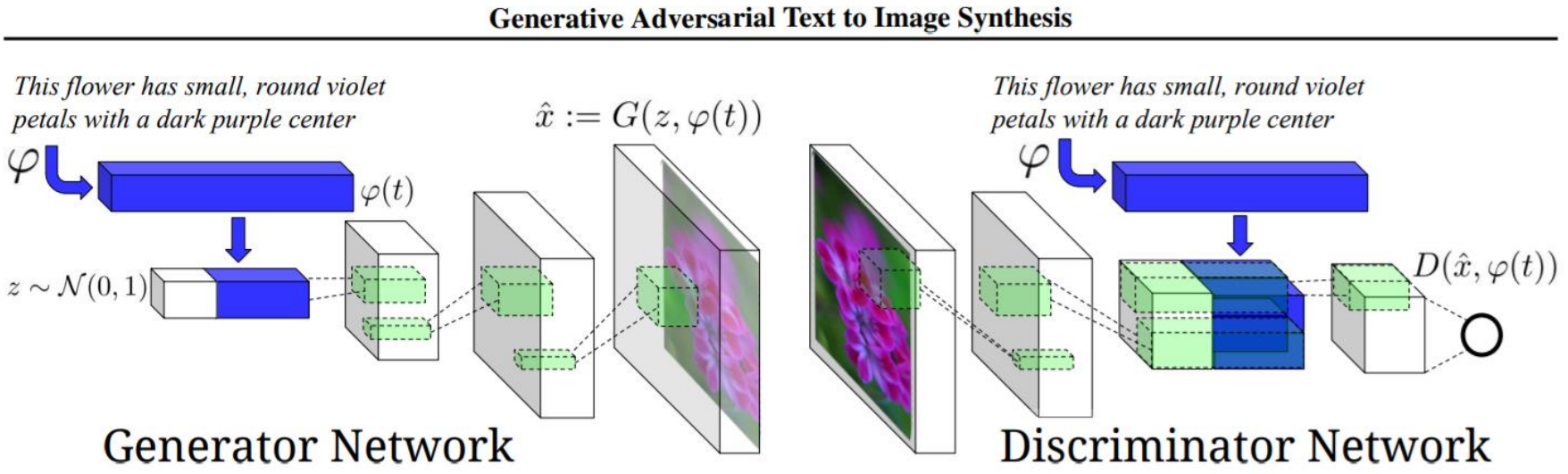
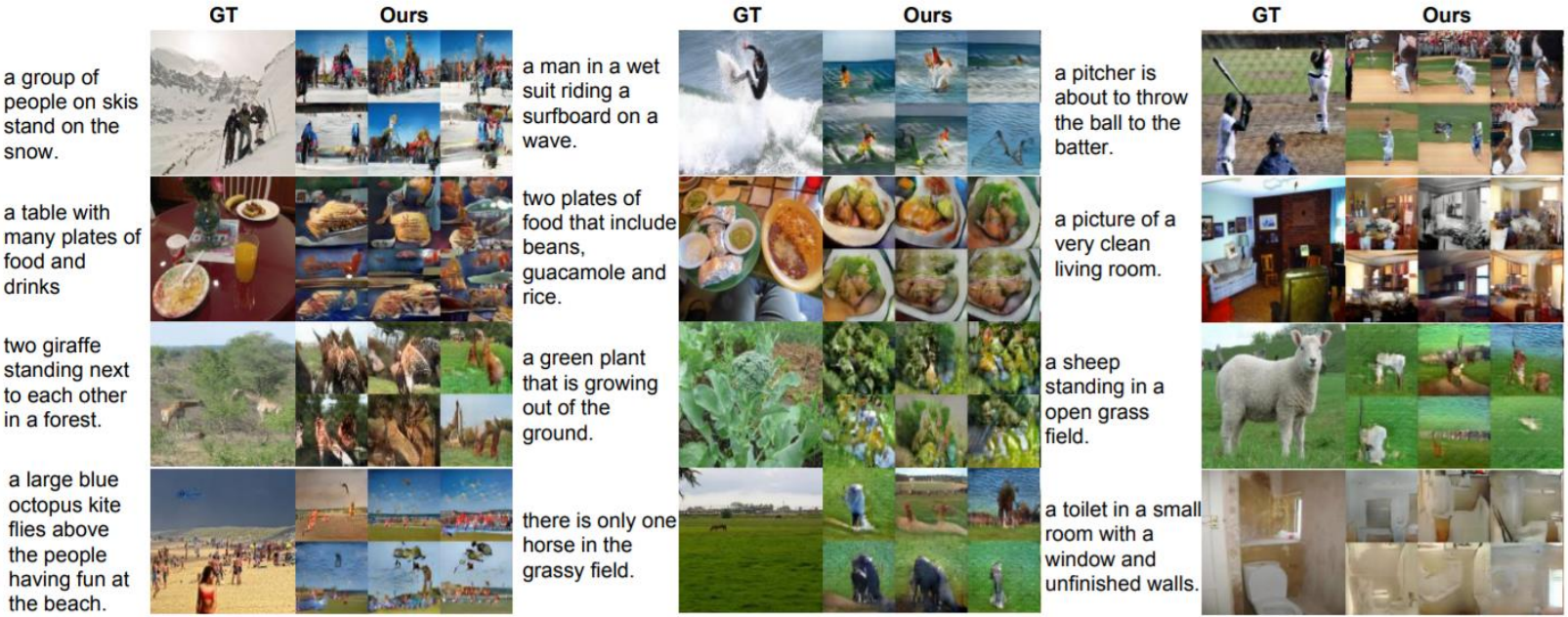


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

Models



텍스트가 들어오면 해당 문장에 맞는
이미지를 생성해내는 conditional GAN

Models

pix2pix

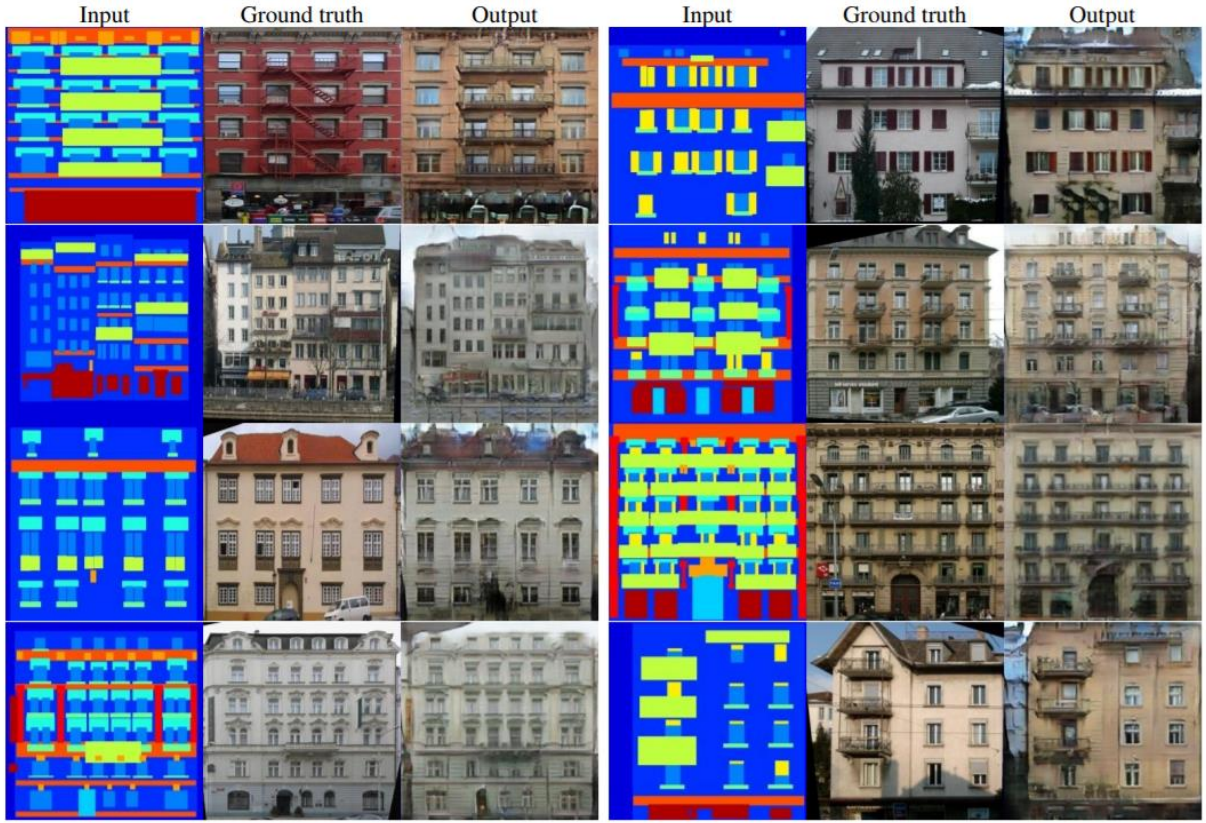
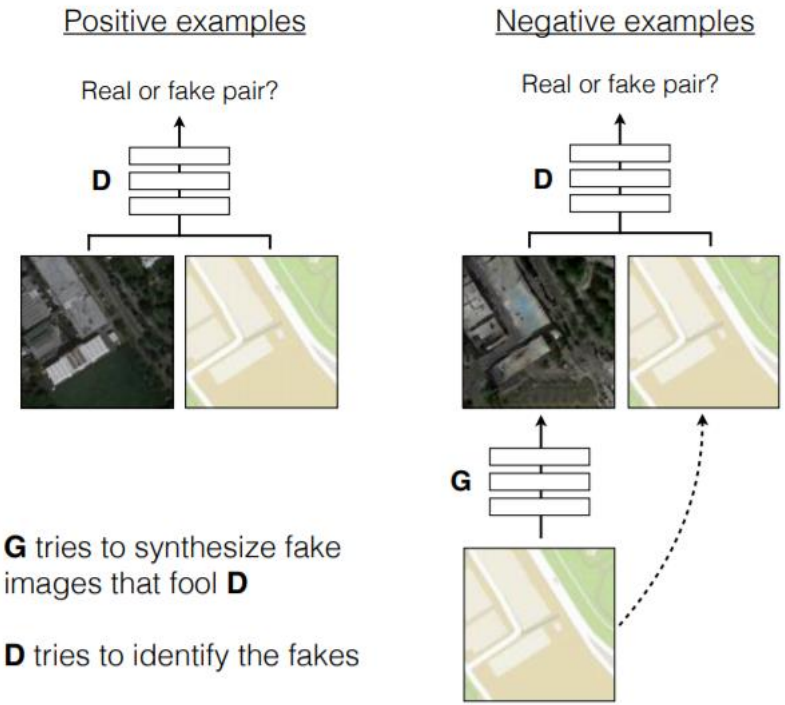


Image-to-Image Translation with Conditional Adversarial Networks

Models



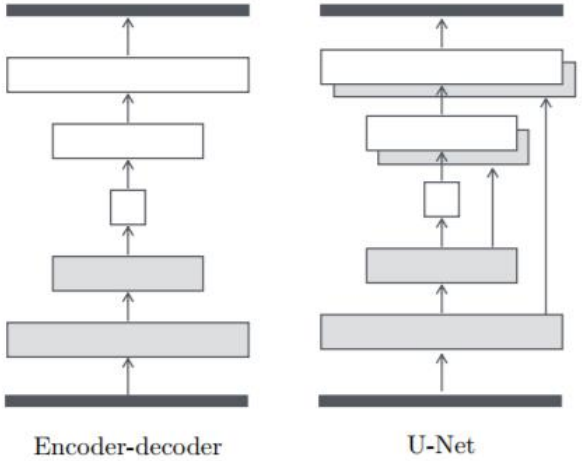
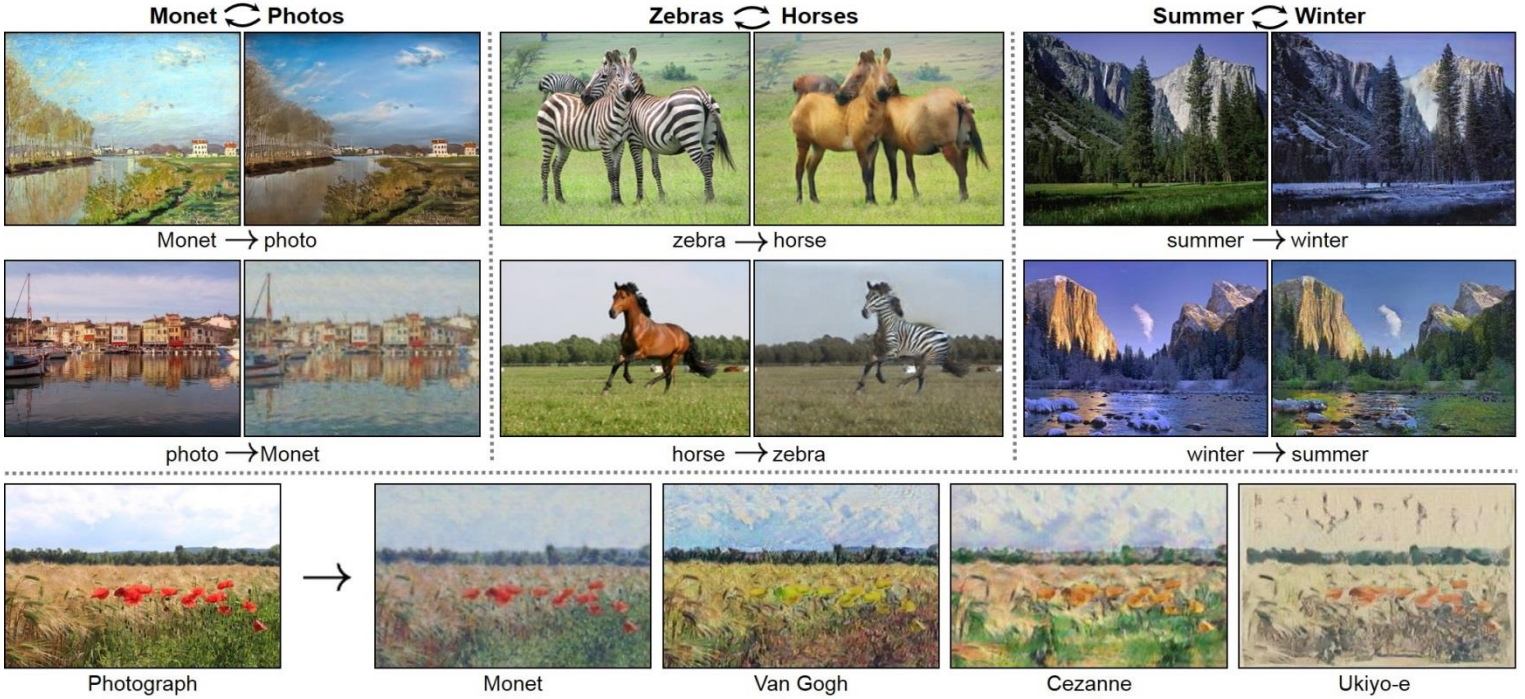


Figure 3: Two choices for the architecture of the generator. The "U-Net" [34] is an encoder-decoder with skip connections between mirrored layers in the encoder and decoder stacks.

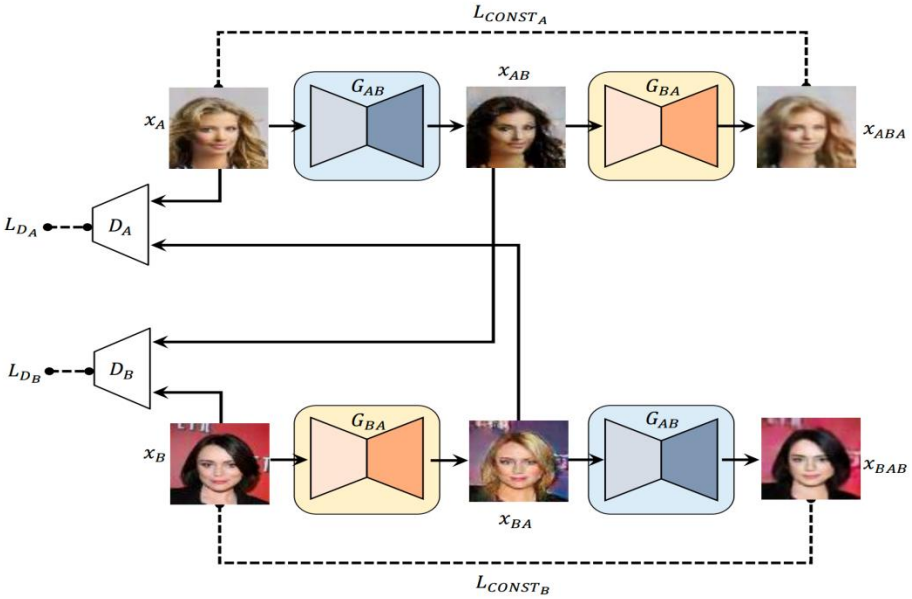
입력으로 이미지를 받기 때문에 Generator -가 Encoder-Decoder 형식을 가짐

Models

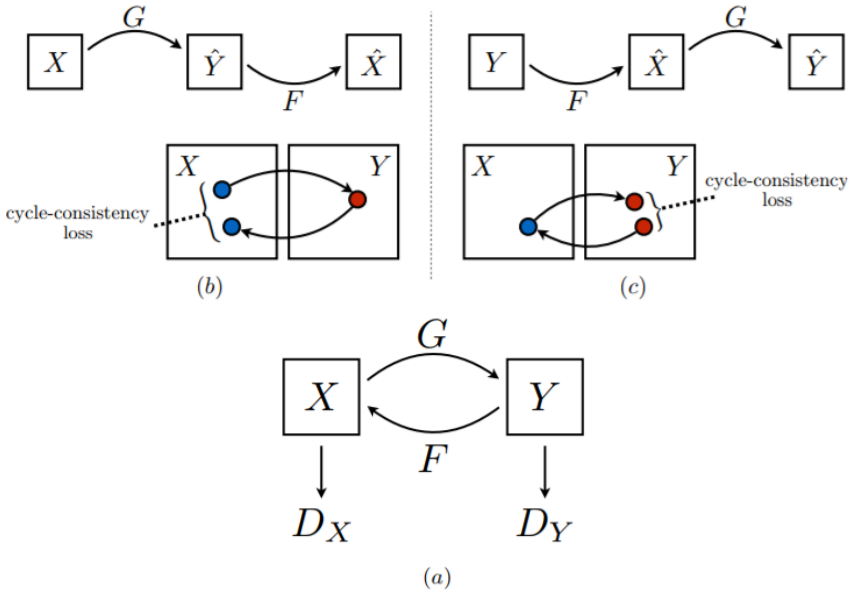


Pair가 있던 pix2pix과 달리 Unpaired Image to Image Translation

Models



DiscoGAN



CycleGAN

Models

Style Transfer

Image to Photograph

Models

Progressive Growing of GANs

https://youtu.be/XOxxPcy5Gr4?t=1m21s

Models

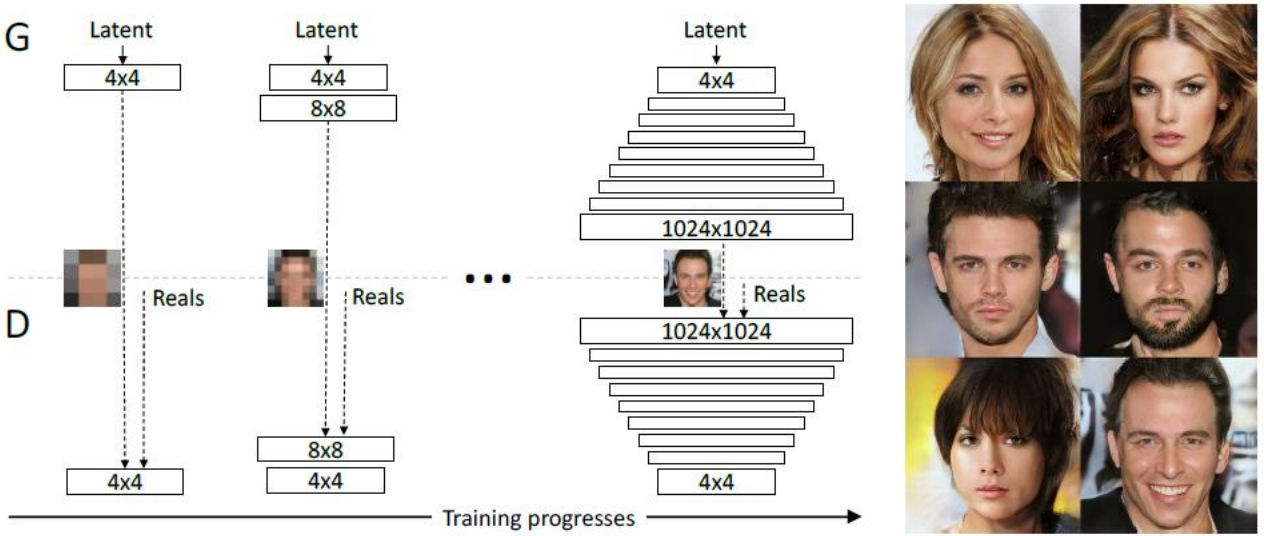


Figure 1: Our training starts with both the generator (G) and discriminator (D) having a low spatial resolution of 4×4 pixels. As the training advances, we incrementally add layers to G and D, thus increasing the spatial resolution of the generated images. All existing layers remain trainable throughout the process. Here $N \times N$ refers to convolutional layers operating on $N \times N$ spatial resolution. This allows stable synthesis in high resolutions and also speeds up training considerably.

Models

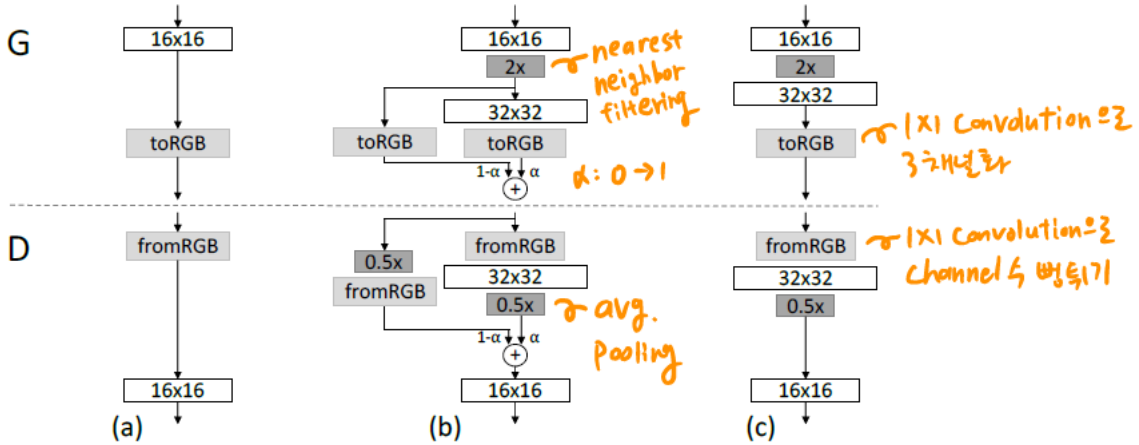


Figure 2: When doubling the resolution of the generator (G) and discriminator (D) we fade in the new layers smoothly. This example illustrates the transition from 16×16 images (a) to 32×32 images (c). During the transition (b) we treat the layers that operate on the higher resolution like a residual block, whose weight α increases linearly from 0 to 1. Here $2\times$ and $0.5\times$ refer to doubling and halving the image resolution using nearest neighbor filtering and average pooling, respectively. The toRGB represents a layer that projects feature vectors to RGB colors and fromRGB does the reverse; both use 1×1 convolutions. When training the discriminator, we feed in real images that are downscaled to match the current resolution of the network. During a resolution transition, we interpolate between two resolutions of the real images, similarly to how the generator output combines two resolutions.

Models

소개한 예시 외에도 엄청 많음

Papers

Theory & Machine Learning

- A Connection between Generative Adversarial Networks, Inverse Reinforcement Learning, and Energy-Based Models [arXiv]
- A General Retraining Framework for Scalable Adversarial Classification [Paper]
- Activation Maximization Generative Adversarial Nets [arXiv]
- AdaGAN: Boosting Generative Models [arXiv]
- Adversarial Autoencoders [arXiv]
- Adversarial Discriminative Domain Adaptation [arXiv]
- Adversarial Generator-Encoder Networks [arXiv]
- Adversarial Feature Learning [arXiv] [Code]
- Adversarially Learned Inference [arXiv] [Code]
- AE-GAN: adversarial eliminating with GAN [arXiv]
- An Adversarial Regularisation for Semi-Supervised Training of Structured Output Neural Networks [arXiv]
- Associative Adversarial Networks [arXiv]
- Autoencoding beyond pixels using a learned similarity metric [arXiv]
- Bayesian Conditional Generative Adverserial Networks [arXiv]
- Bayesian GAN [arXiv]
- BEGAN: Boundary Equilibrium Generative Adversarial Networks [Paper] [arXiv] [Code]
- Binary Generative Adversarial Networks for Image Retrieval [arXiv]
- Boundary-Seeking Generative Adversarial Networks [arXiv] [Code]
- CausalGAN: Learning Causal Implicit Generative Models with Adversarial Training [arXiv]
- Comparison of Maximum Likelihood and GAN-based training of Real NVPs [arXiv]
- Conditional CycleGAN for Attribute Guided Face Image Generation [arXiv]
- Conditional Generative Adversarial Nets [arXiv] [Code]
- LR-GAN: Layered Recursive Generative Adversarial Networks for Image Generation [arXiv]
- MAGAN: Margin Adaptation for Generative Adversarial Networks [arXiv] [Code]
- Maximum-Likelihood Augmented Discrete Generative Adversarial Networks [arXiv]
- McGan: Mean and Covariance Feature Matching GAN [arXiv]
- Message Passing Multi-Agent GANs [arXiv]
- Mode Regularized Generative Adversarial Networks [arXiv] [Code]
- Multi-Agent Diverse Generative Adversarial Networks [arXiv]
- Multi-Generator Gernerative Adversarial Nets [arXiv]
- Objective-Reinforced Generative Adversarial Networks (ORGAN) for Sequence Generation Models [arXiv]
- On the effect of Batch Normalization and Weight Normalization in Generative Adversarial Networks [arXiv]
- On the Quantitative Analysis of Decoder-Based Generative Models [arXiv]
- Optimizing the Latent Space of Generative Networks [arXiv]
- PixelGAN Autoencoders [arXiv]
- SegAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation [arXiv]
- SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient [arXiv]
- Simple Black-Box Adversarial Perturbations for Deep Networks [Paper]
- Softmax GAN [arXiv]
- Stabilizing Training of Generative Adversarial Networks through Regularization [arXiv]
- Stacked Generative Adversarial Networks [arXiv]
- Statistics of Deep Generated Images [arXiv]
- The Cramer Distance as a Solution to Biased Wasserstein Gradients [arXiv]
- Towards Understanding Adversarial Learning for Joint Distribution Matching [arXiv]
- Training generative neural networks via Maximum Mean Discrepancy optimization [arXiv]
- Triple Generative Adversarial Nets [arXiv]
- Unrolled Generative Adversarial Networks [arXiv]
- Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks [arXiv] [Code] [Code] [Code] [Code] [Code]
- Wasserstein GAN [arXiv] [Code] [Code]

https://github.com/nightrome/really-awesome-gan

GAN Hacks

GAN 학습 잘되게 하는 꿀팁

1. Input 정규화: -1~1의 값으로 정규화 시켜서 넣는다.

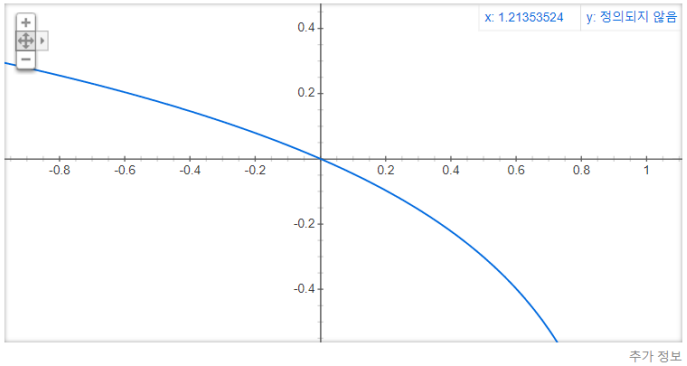
GAN Hacks

GAN 학습 잘되게 하는 꿀팁

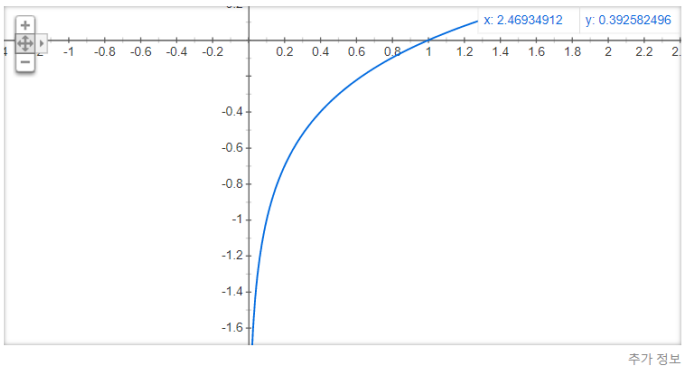
1. Input 정규화: -1~1의 값으로 정규화 시켜서 넣는다.
2. Modified Loss Function을 사용한다.

사실 $\log\left(1-\mathrm{D}(\mathrm{G}(\mathrm{z}))\right)$를 최소화하는것은 $\log\left(D(G(z))\right)$를 $maximize$ 하는것과 같음
같은 의미지만 후자의 gradient값들이 더 크기 때문에 학습이 더 잘됨

log(1-x) 그래프



log(x) 그래프



GAN Hacks

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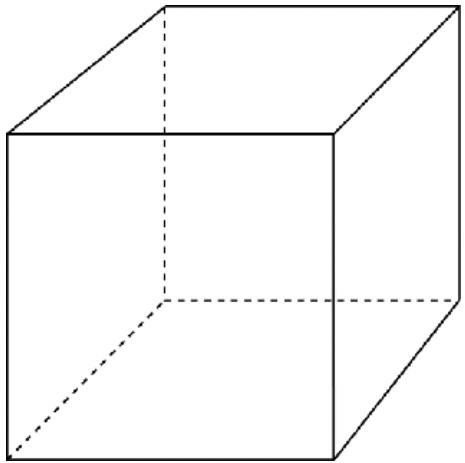
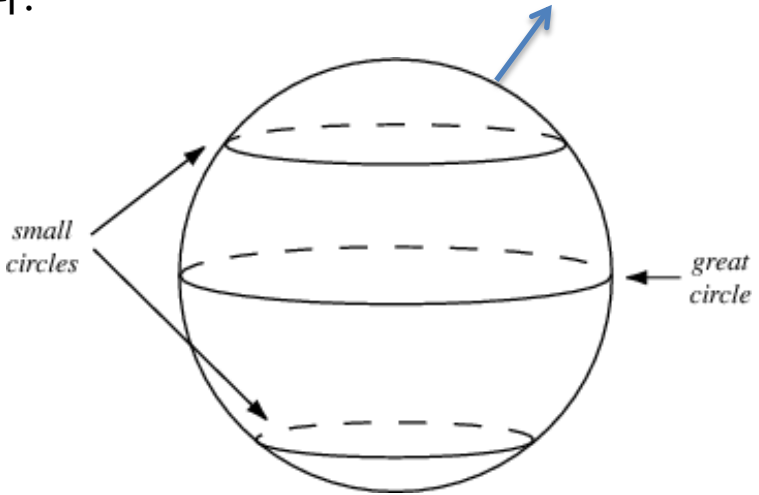
3. Z를 Normal Gaussian에서 뽑는다.

Interpolation 관점으로
생각해보면 이해할 수 있음



Uniform Distribution



Normal Distribution

https://github.com/soumith/ganhacks

GAN Hacks

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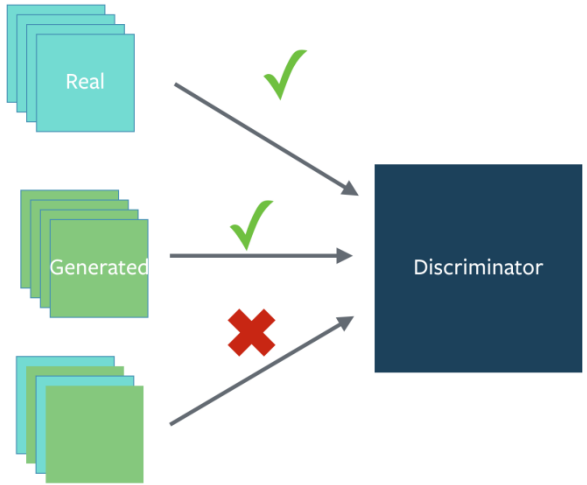

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GAN Hacks

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GAN Hacks

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6. Label Smoothing or Noisy Label

Discriminator가 헷갈리게 Real data에 대해서 1이 아닌 1~0.7정도의 라벨을 주거나 확률적으로 Real Data임에도 라벨을 0으로 줘서 헷갈리게 만들기

https://github.com/soumith/ganhacks

GAN Hacks

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6. Label Smoothing or Noisy Label
7. Discriminator input에 noise를 추가했다가 점차 없앰

이 방법 역시 학습 밸런스를 위해서 쓰는 방법

https://github.com/soumith/ganhacks

GAN Hacks

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8. Adam optimizer 사용

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GAN Hacks

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8. Adam optimizer 사용
9. Generator 몇 개 레이어에 Drop Out 적용

pix2pix 논문에서 사용한 방법

https://github.com/soumith/ganhacks

GAN Hacks

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⋮

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Q&A