Deep Convolutional Generative Adversarial Networks

DEEP LEARNING BASED ANOMALY DETECTION MODELING (GEK6207.01-00)
Coding practice

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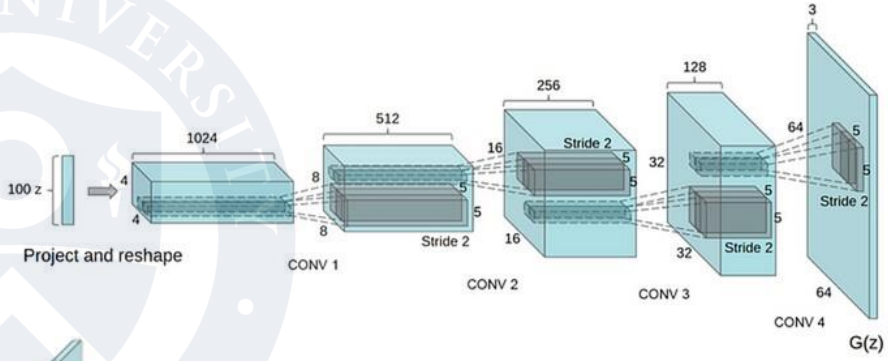
1 DCGAN

What is a DCGAN?

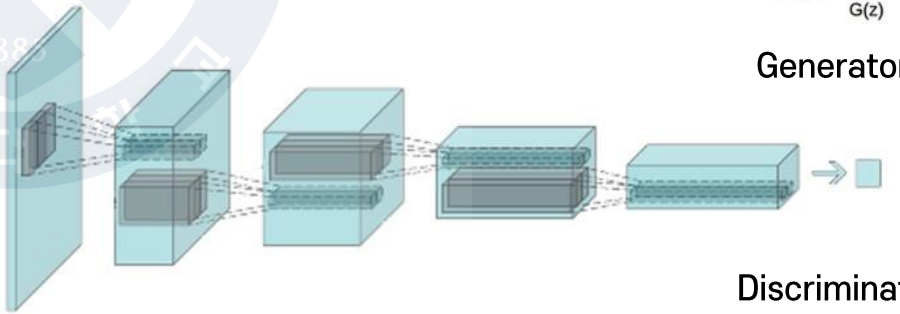
A DCGAN is a direct extension of the GAN, except that it explicitly uses convolutional and convolutional-transpose layers in the discriminator and generator, respectively.

The **generator** is comprised of convolutional-transpose layers, batch norm layers, and ReLU activations. The input is a latent vector, that is drawn from a standard normal distribution and the output is a 3x64x64 RGB image.

The **discriminator** is made up of strided convolution layers, batch norm layers, and LeakyReLU activations. The input is a 3x64x64 input image and the output is a scalar probability that the input is from the real data distribution.



Generator



Discriminator

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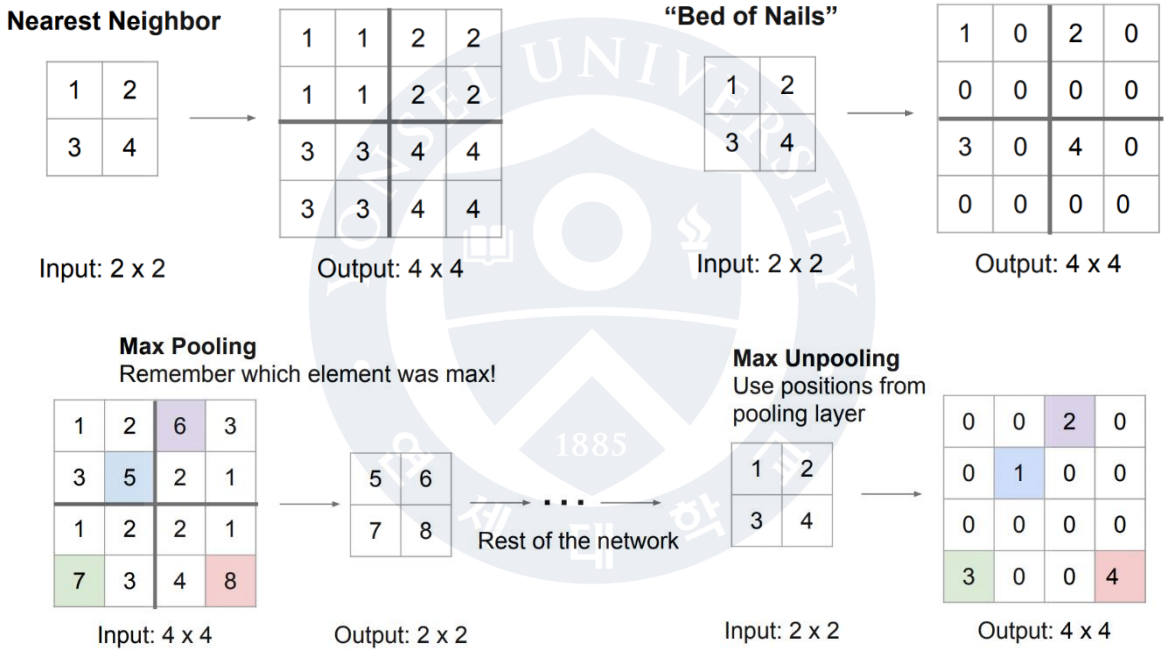
Upsampling



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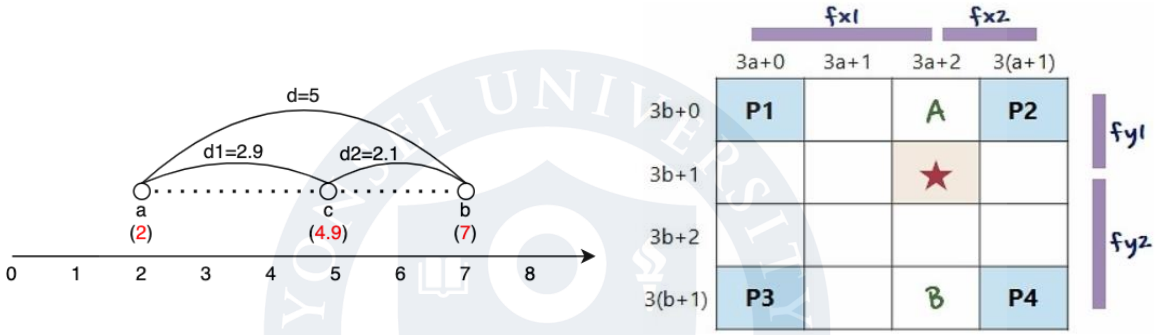
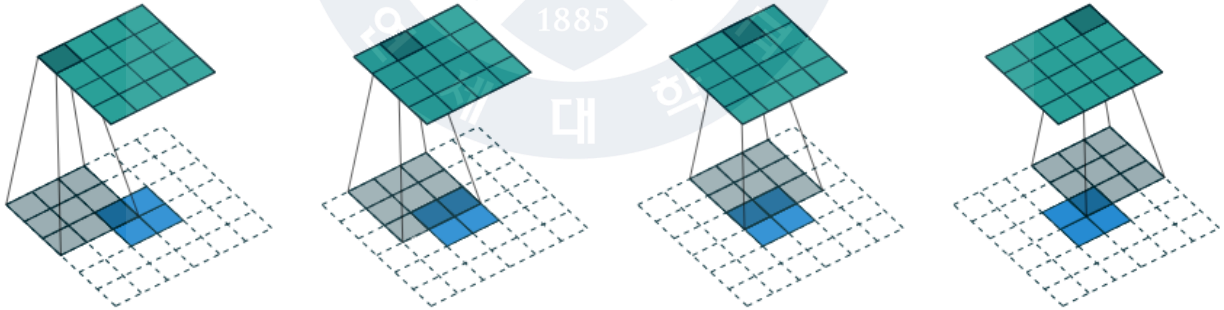
Upsampling



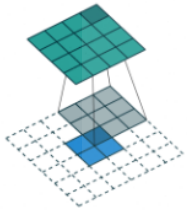
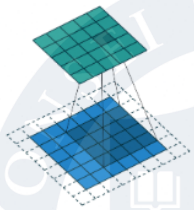
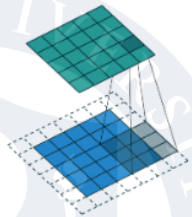
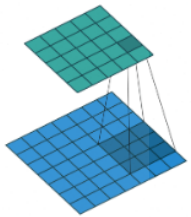
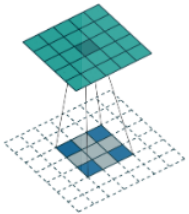
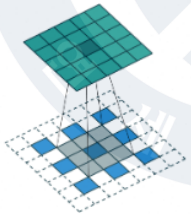
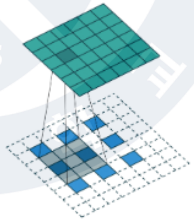
Linear Interpolation



Transposed Convolution

1 DCGAN

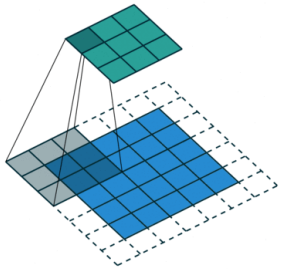
- Transposed convolution

			
No padding, no strides, transposed	Arbitrary padding, no strides, transposed	Half padding, no strides, transposed	Full padding, no strides, transposed
			
No padding, strides, transposed	Padding, strides, transposed	Padding, strides, transposed (odd)	

https://github.com/vdumoulin/conv_arithmetic

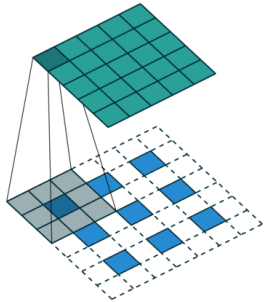
1 DCGAN

Convolution output size



in = 5
out = 3
padding (p) = 1
stride (s) = 2
kernel_size (k) = 3

$$\text{Out} = \left\lfloor \frac{\text{in} + 2*\text{padding} - \text{kernel\_size}}{\text{stride}} \right\rfloor + 1$$

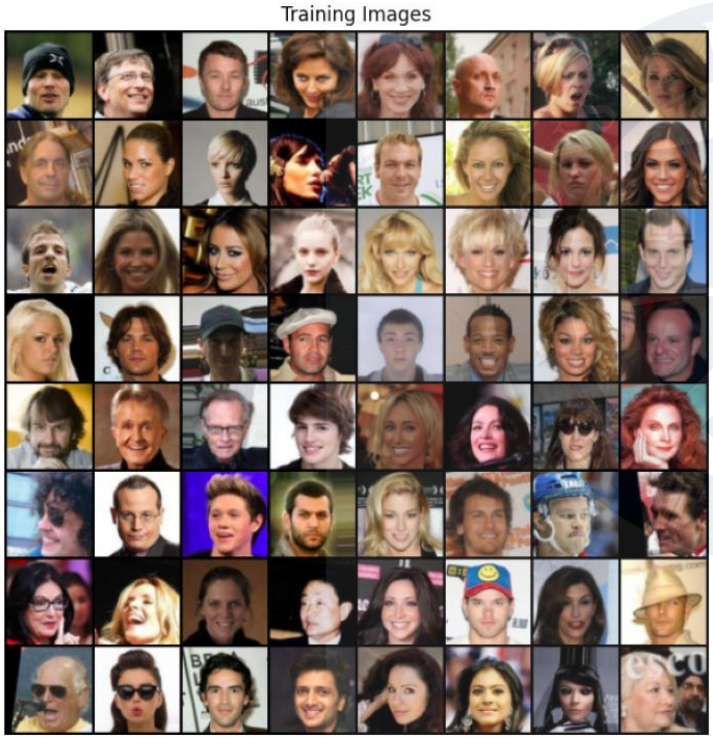


in = 3
out = 5
padding (p) = 1
stride (s) = 2
kernel_size (k) = 3

$$\text{Out} = (\text{in} - 1) * \text{stride} - 2 * \text{padding} + \text{kernel\_size}$$

1 DCGAN

Celeb-A Faces dataset



· Celeb-A Faces dataset is a large collection of celebrity facial images used for tasks like facial recognition and generative modeling.

· It includes over 200,000 diverse celebrity images.

1 DCGAN

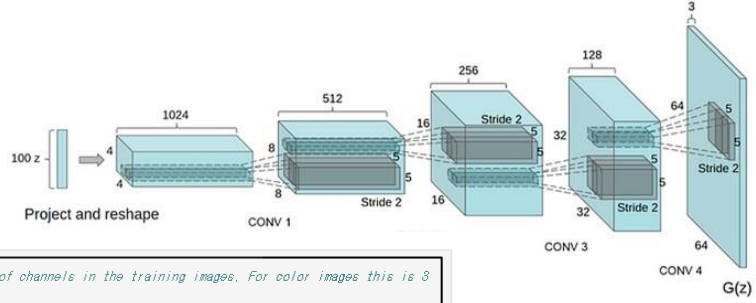
Inputs Code

In [44]:

```
# Root directory for dataset
dataroot = "data/celeba"

# Number of workers for dataloader
workers = 2

# Batch size during training
batch_size = 128

# Spatial size of training images. All images will be resized to this
#   size using a transformer.
image_size = 64

# Number of channels in the training images. For color images this is 3
nc = 3

# Size of z latent vector (i.e. size of generator input)
nz = 100

# Size of feature maps in generator
ngf = 64

# Size of feature maps in discriminator
ndf = 64

# Number of training epochs
num_epochs = 5

# Learning rate for optimizers
lr = 0.0002

# Beta1 hyperparameter for Adam optimizers
beta1 = 0.5

# Number of GPUs available. Use 0 for CPU mode.
ngpu = 1
```

1 DCGAN

Generator Code



In [47]:

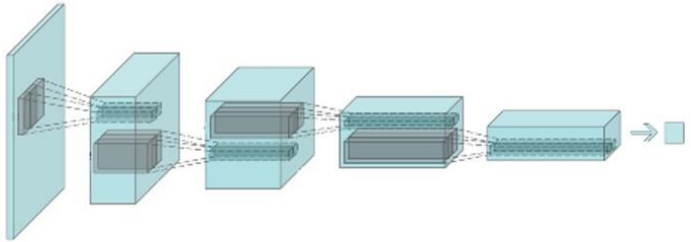
```python
# Generator Code

class Generator(nn.Module):
    def __init__(self, ngpu):
        super(Generator, self).__init__()
        self.ngpu = ngpu
        self.main = nn.Sequential(
            # input is Z, going into a convolution
            nn.ConvTranspose2d( nz, ngf * 8, 4, 1, 0, bias=False),
            nn.BatchNorm2d(ngf * 8),
            nn.ReLU(True),
            # state size. ``(ngf*8) x 4 x 4``
            nn.ConvTranspose2d(ngf * 8, ngf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 4),
            nn.ReLU(True),
            # state size. ``(ngf*4) x 8 x 8``
            nn.ConvTranspose2d( ngf * 4, ngf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 2),
            nn.ReLU(True),
            # state size. ``(ngf*2) x 16 x 16``
            nn.ConvTranspose2d( ngf * 2, ngf, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf),
            nn.ReLU(True),
            # state size. ``(ngf) x 32 x 32``
            nn.ConvTranspose2d( ngf, nc, 4, 2, 1, bias=False),
            nn.Tanh()
            # state size. ``(nc) x 64 x 64``
        )

    def forward(self, input):
        return self.main(input)
```

```python
# Number of channels in the training images. For color images this is 3
nc = 3

# Size of z latent vector (i.e. size of generator input)
nz = 100

# Size of feature maps in generator
ngf = 64

# Size of feature maps in discriminator
ndf = 64
```

CLASS torch.nn.ConvTranspose2d(*in_channels, out_channels, kernel_size, stride=1, padding=0, output_padding=0, groups=1, bias=True, dilation=1, padding_mode='zeros', device=None, dtype=None*) [SOURCE]

```
Generator(
  (main): Sequential(
    (0): ConvTranspose2d(100, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (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, track_running_stats=True)
    (5): ReLU(inplace=True)
    (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, track_running_stats=True)
    (8): ReLU(inplace=True)
    (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, track_running_stats=True)
    (11): ReLU(inplace=True)
    (12): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (13): Tanh()
  )
)
```

1 DCGAN



Discriminator Code

In [49]:

```
class Discriminator(nn.Module):
    def __init__(self, ngpu):
        super(Discriminator, self).__init__()
        self.ngpu = ngpu
        self.main = nn.Sequential(
            # input is ``(nc) x 64 x 64``
            nn.Conv2d(nc, ndf, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. ``(ndf) x 32 x 32``
            nn.Conv2d(ndf, ndf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 2),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. ``(ndf*2) x 16 x 16``
            nn.Conv2d(ndf * 2, ndf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 4),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. ``(ndf*4) x 8 x 8``
            nn.Conv2d(ndf * 4, ndf * 8, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 8),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. ``(ndf*8) x 4 x 4``
            nn.Conv2d(ndf * 8, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
        )

    def forward(self, input):
        return self.main(input)
```

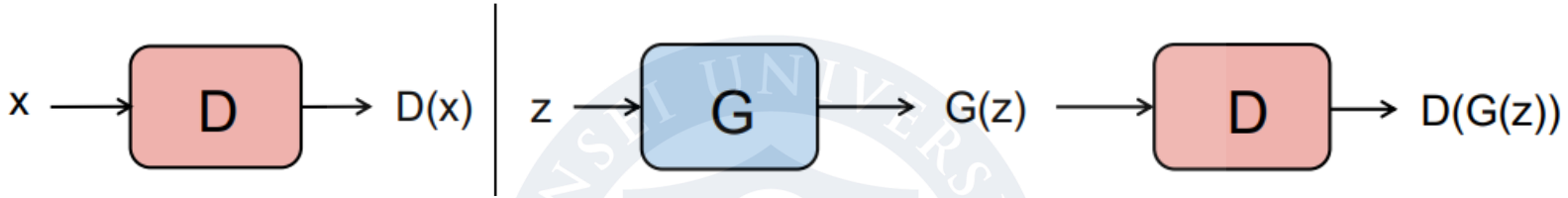
```
# Number of channels in the training images. For color images this is 3
nc = 3

# Size of z latent vector (i.e. size of generator input)
nz = 100

# Size of feature maps in generator
ngf = 64

# Size of feature maps in discriminator
ndf = 64
```

CLASS torch.nn.Conv2d(*in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True, padding_mode='zeros', device=None, dtype=None*) [SOURCE]

```
Discriminator(
  (main): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): LeakyReLU(negative_slope=0.2, inplace=True)
    (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, track_running_stats=True)
    (4): LeakyReLU(negative_slope=0.2, inplace=True)
    (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, track_running_stats=True)
    (7): LeakyReLU(negative_slope=0.2, inplace=True)
    (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, track_running_stats=True)
    (10): LeakyReLU(negative_slope=0.2, inplace=True)
    (11): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (12): Sigmoid()
  )
)
```

1 DCGAN

Loss Function



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

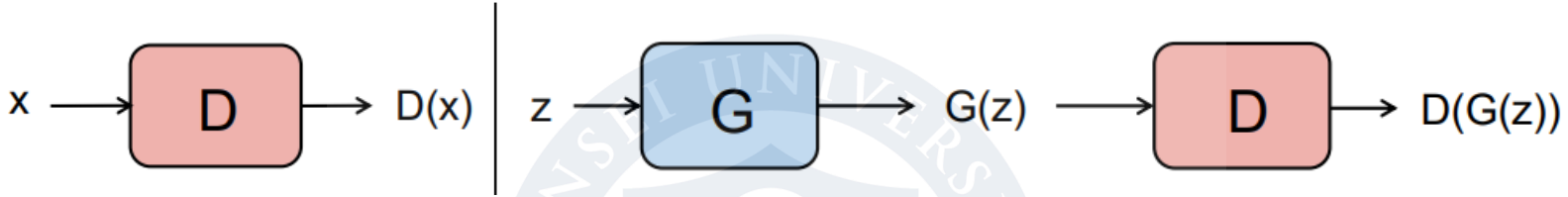
Adversarial Training

Part 1 – Train the Discriminator

Part 2 – Train the Generator

1 DCGAN

Loss Function

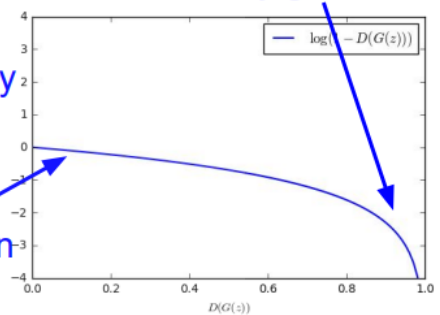


$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

In practice, optimizing this generator objective does not work well!

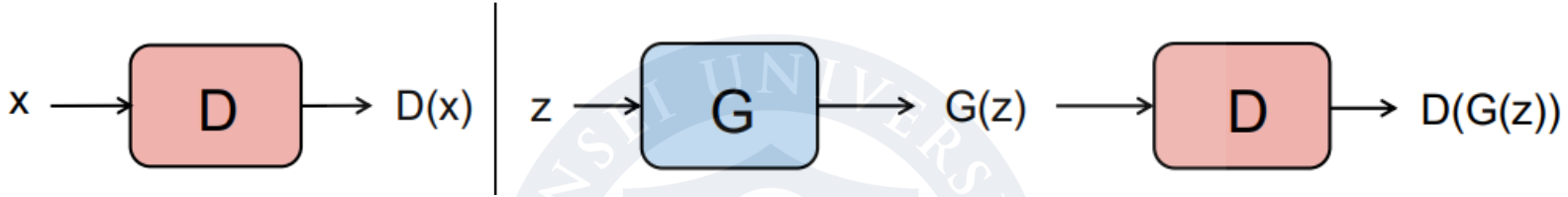
Gradient signal dominated by region where sample is already good

When sample is likely fake, want to learn from it to improve generator. But gradient in this region is relatively flat!



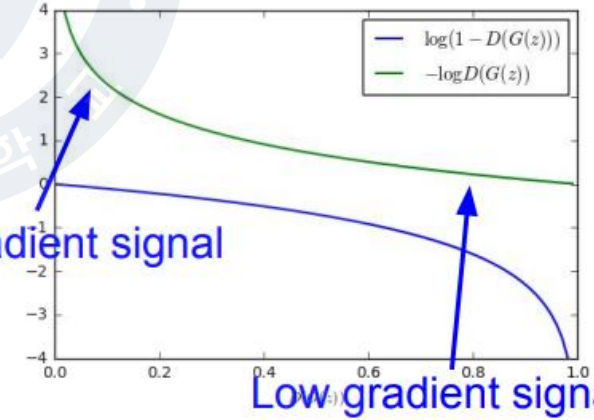
1 DCGAN

Loss Function



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

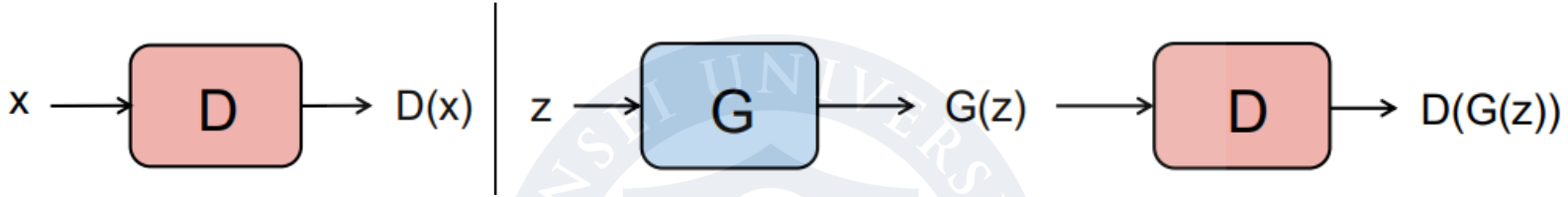
$$\max_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$



Instead of minimizing likelihood of discriminator being correct, now maximize likelihood of discriminator being wrong.
Same objective of fooling discriminator, but now higher gradient signal for bad samples => works much better!

1 DCGAN

Loss Function



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

log maximization (=) negative log minimization

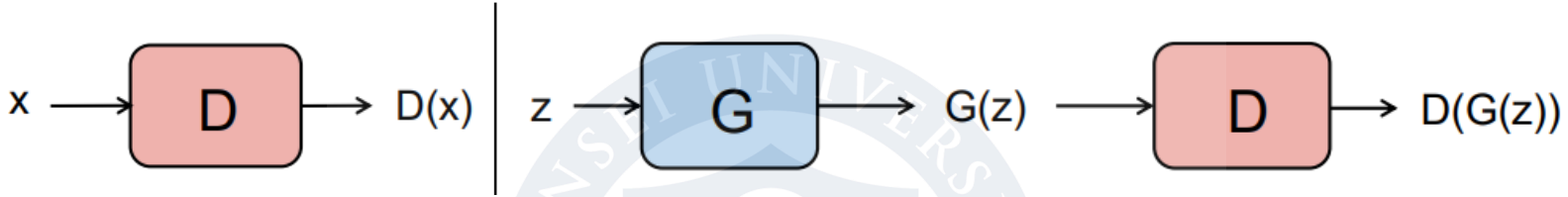
$$-(y_i \log(p_i) + (1 - y_i)\log(1 - p_i))$$

$\min\ -1\log D(x)$ $\min\ -(1-0)\log(1 - D(G(z)))$

```
criterion = nn.BCELoss()

# train D
loss = criterion(D(x), 1) + criterion(D(G(z)), 0)
loss.backward()
d_optimizer.step()

# train G
loss = criterion(D(G(z)), 1)
loss.backward()
g_optimizer.step()
```

1 DCGAN

Loss Function



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

$$\max_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

-> negative log minimization

$$-(y_i \log(p_i) + (1 - y_i) \log(1 - p_i))$$

$$\min \; -1\log D(G(z))$$

```
criterion = nn.BCELoss()

# train D
loss = criterion(D(x), 1) + criterion(D(G(z)), 0)
loss.backward()
d_optimizer.step()

# train G
loss = criterion(D(G(z)), 1)
loss.backward()
g_optimizer.step()
```

1 DCGAN

Loss Function Code

In [53]:

```
# Initialize the ``BCELoss`` function
criterion = nn.BCELoss()

# Create batch of latent vectors that we will use to visualize
#  the progression of the generator
fixed_noise = torch.randn(64, nz, 1, 1, device=device)

# Establish convention for real and fake labels during training
real_label = 1.
fake_label = 0.

# Setup Adam optimizers for both G and D
optimizerD = optim.Adam(netD.parameters(), lr=lr, betas=(beta1, 0.999))
optimizerG = optim.Adam(netG.parameters(), lr=lr, betas=(beta1, 0.999))
```

```
############################
# (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
###########################
## Train with all-real batch
netD.zero_grad()
# Format batch
real_cpu = data[0].to(device)
b_size = real_cpu.size(0)
label = torch.full((b_size,), real_label, dtype=torch.float, device=device)
# Forward pass real batch through D
output = netD(real_cpu).view(-1)
# Calculate loss on all-real batch
errD_real = criterion(output, label)
# Calculate gradients for D in backward pass
errD_real.backward()
D_x = output.mean().item()
```

```
## Train with all-fake batch
# Generate batch of latent vectors
noise = torch.randn(b_size, nz, 1, 1, device=device)
# Generate fake image batch with G
fake = netG(noise)
label.fill_(fake_label)
# Classify all fake batch with D
output = netD(fake.detach()).view(-1)
# Calculate D's loss on the all-fake batch
errD_fake = criterion(output, label)
# Calculate the gradients for this batch, accumulated (summed) with previous gradients
errD_fake.backward()
D_G_z1 = output.mean().item()
# Compute error of D as sum over the fake and the real batches
errD = errD_real + errD_fake
# Update D
optimizerD.step()
```

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

1 DCGAN

Loss Function Code

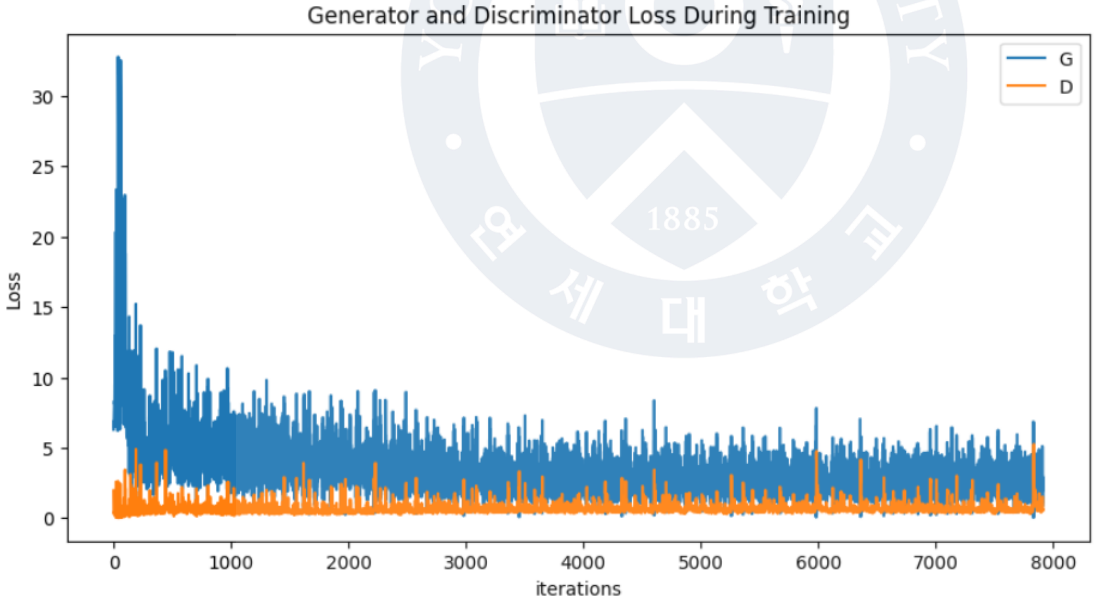
$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

```
###############################
# (2) Update G network: maximize log(D(G(z)))
###############################
netG.zero_grad()
label.fill_(real_label)  # fake labels are real for generator cost
# Since we just updated D, perform another forward pass of all-fake batch through D
output = netD(fake).view(-1)
# Calculate G's loss based on this output
errG = criterion(output, label)
# Calculate gradients for G
errG.backward()
D_G_z2 = output.mean().item()
# Update G
optimizerG.step()
```

1 DCGAN

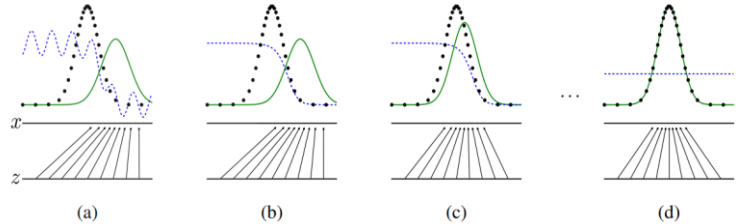
Loss During Training

In [55]:
```
plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses,label="G")
plt.plot(D_losses,label="D")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



1 DCGAN

Results



Real Images

Fake Images

1 DCGAN

Github Code

ad-yonsei

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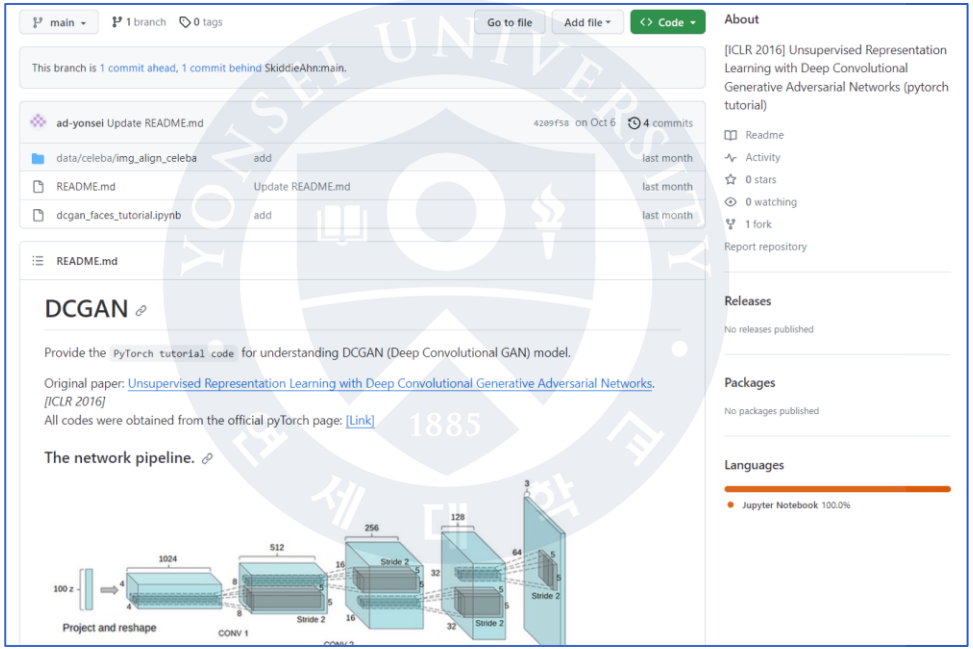
DEEP LEARNING BASED ANOMALY DETECTION MODELING (GEK6207.01-00), Yonsei University

Block or Report



https://github.com/ad-yonsei/Code-DCGAN

https://pytorch.org/tutorials/beginner/dcgan_faces_tutorial.html

1 DCGAN

References

- CS231n: Deep Learning for Computer Vision
  Lecture 13 | Generative Models (https://www.youtube.com/watch?v=5WoItGTWV54)
- Generative Adversarial Networks (NAVER D2)
  (https://youtu.be/odpjk7_tGY0?si=d3zvilLO6HUCtPu8)
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- Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015).
- Calculating the Output Size of Convolutions and Transpose Convolutions
  (https://makeyourownneuralnetwork.blogspot.com/2020/02/calculating-output-size-of-convolutions.html)

Thank You

DCGAN - coding practice

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