


DCGAN in PyTorch

• get data

```
import torch
```

```
from torchvision import datasets, transforms
```

```
transform = transforms.ToTensor() # transforming to tensor
```

```
train_data = datasets.SVHN(root='data', split='train',  
                              dataset download=True, transform=transform)  
for real-world street numbers
```

```
bsize = 128
```

```
train_loader = torch.utils.data.DataLoader ( dataset=train_data,  
                                              batch_size=bsize,  
                                              shuffle=True,  
                                              num_workers=0)
```

• Pre-processing

```
def scale(x, feature_range=(-1, 1)):
```

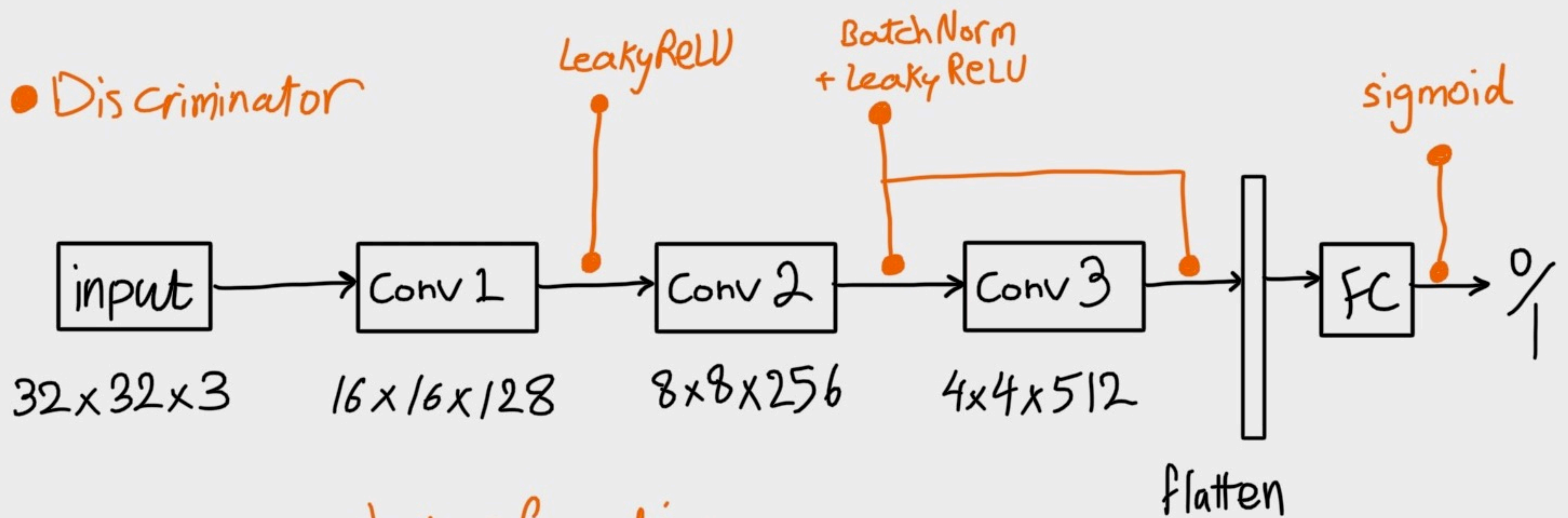
```
    min, max = feature_range
```

```
    x = x * (max - min) + min
```

```
    return x
```

→ scale to feature range

● Discriminator



helper function

```
def conv(in_chan, out_chan, kernel_size,
        stride=2, padding=1, batch_norm=True):
    layers = []
    conv_layer = nn.Conv2d(in_chan, out_chan, kernel_size,
                           stride, padding, bias=False)
    layers.append(conv_layer) → stack them
    if batch_norm:
        layers.append(nn.BatchNorm2d(out_chan) → add batch norm)
    return nn.Sequential(*layers) → create a sequence of layers
```



```
class D(nn.Module):
```

```
    def __init__(self, conv_dim=32):
```

```
        super(D, self).__init__()
```

```
        self.conv_dim = conv_dim
```

```
        # input: 32x32
```

```
16x16: self.conv1 = Conv(3, conv_dim, 4, batch_norm=False)
```

```
8x8: self.conv2 = Conv(conv_dim, conv_dim*2, 4)
```

```
4x4: self.conv3 = Conv(conv_dim*2, conv_dim*4, 4)
```

```
self.fc = nn.Linear(conv_dim*4*4*4, 1)
```

```
def forward(self, x):
```

```
    out = F.leaky_relu(self.conv1(x), 0.2)
```

```
    out = F.leaky_relu(self.conv2(out), 0.2)
```

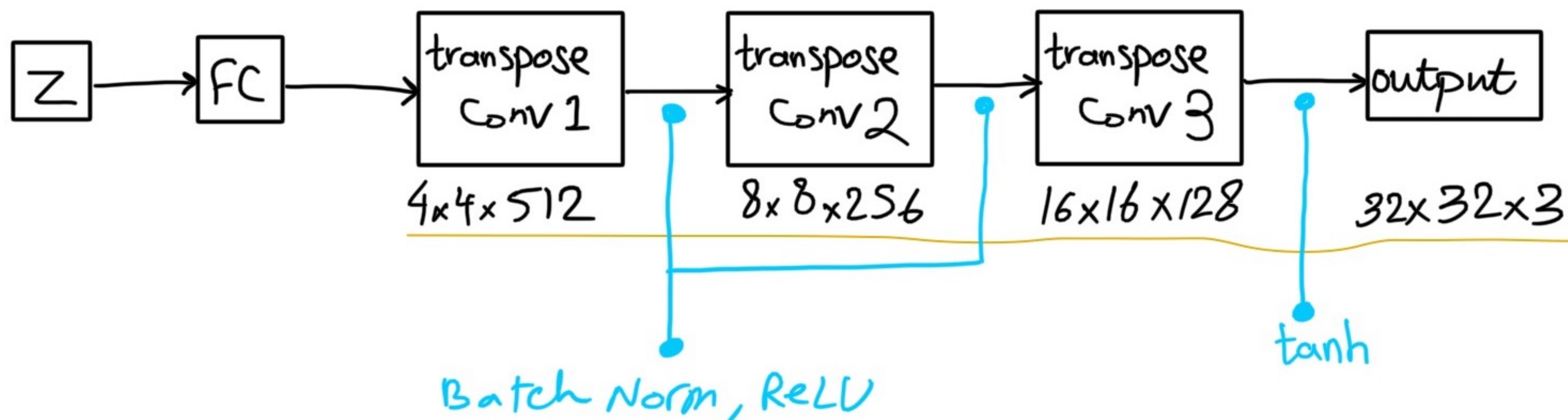
```
    out = F.leaky_relu(self.conv3(out), 0.2)
```

```
    out = out.view(-1, conv_dim*4*4*4)
```

```
    out = self.fc(out)
```

```
    return out
```


• Generator



→ helper to make transpose Conv

```
def deconv(in_chan, out_chan, kernel_size,
           stride=2, padding=1, batch_norm=True):
    layers = []
    conv_layer = nn.ConvTranspose2d(in_chan, out_chan, kernel_size,
                                     only diff stride, padding, bias=False)
    layers.append(conv_layer)

    if batch_norm:
        layers.append(nn.BatchNorm2d(out_chan))

    return nn.Sequential(*layers)
```



```
class G(nn.Module):
```

```
    def __init__(self, z_size, conv_dim = 32):
```

```
        super(G, self).__init__()
```

```
        self.conv_dim = conv_dim
```

this should
gen
enough output

```
        self.fc = nn.Linear(z_size, conv_dim * 4 * 4 * 4)
```

transpose
Conv
layers

```
        self.tconv1 = deconv(conv_dim * 4, conv_dim * 2, 4)
```

```
        self.tconv2 = deconv(conv_dim * 2, conv_dim, 4)
```

```
        self.tconv3 = deconv(conv_dim, 3, 4, batch_norm=False)
```

```
    def forward(self, x):
```

```
        out = self.fc(x)
```

```
        out = out.view(-1, self.conv_dim * 4, 4, 4)
```

batch size
depth

```
        out = F.relu(self.tconv1(out))
```

```
        out = F.relu(self.tconv2(out))
```

```
        out = F.tanh(self.tconv3(out))
```

```
    return out
```

32x32x3

- glue D and G together

conv_dim = 32

z_size = 100

d = D(conv_dim)

g = G(z_size, conv_dim)

is_gpu = torch.cuda.is_available()

if is_gpu:

g.cuda()

d.cuda()

- define losses

def real_loss(D_out, smooth=False):

b = D_out.size(0)

if smooth:

labels = torch.ones(b) * 0.9

else:

labels = torch.ones(b)

if is_gpu: labels = labels.cuda()

criterion = nn.BCEWithLogitsLoss()

return criterion(D_out.squeeze(), labels)


```
def real_loss (D_out):
```

```
    b = D_out.size(0)
```

```
    labels = torch.zeros(b)
```

```
    if is_gpu: labels = labels.cuda()
```

```
    criterion = nn.BCEWithLogitsLoss()
```

```
    return criterion(D_out.squeeze(), labels)
```

• define optimizer

```
lr, beta1, beta2 = 0.0002, 0.5, 0.999 → from a paper  
or so experiment
```

```
d_opt = optim.Adam(d.parameters(), lr, [beta1, beta2])
```

```
g_opt = optim.Adam(g.parameters(), lr, [beta1, beta2])
```

• Train the models

```
d.train()
```

```
g.train()
```

```
for epoch in range(epochs):
```

```
    for idx, (real_im, —) in enumerate(train_loader):
```

```
        bsize = real_im.size(0)
```

```
        real_im = scale(real_im)
```


discriminator

```
d_optim.zero_grad()
```

```
d_real = d(real_images)
```

```
d_real_loss = real_loss(d_real, smooth=True)
```

seems to be better w/o smoothing!

```
z = np.random.uniform(-1, 1, size=(batch_size, z_size))
```

```
Z = torch.from_numpy(z).float()
```

```
fake_images = G(z)
```

```
d_fake = d(fake_images)
```

```
d_fake_loss = fake_loss(d_fake)
```

```
d_loss = d_real_loss + d_fake_loss
```

```
d_loss.backward()
```

```
d_optim.step()
```


generator

`g_optim.zero_grad()`

`z = np.random.uniform(-1, 1, size=(batch_size, z_size))`

`Z = torch.from_numpy(z).float()`

`fake_images = g(z)`

`d_fake = d(fake_images)`

`g_loss = real_loss(d_fake)`

`g_loss.backward()`

`g_optim.step()`

`losses.append((d_loss.item(), g_loss.item()))`

generated ← Samples.append(G(fixed_z))
images