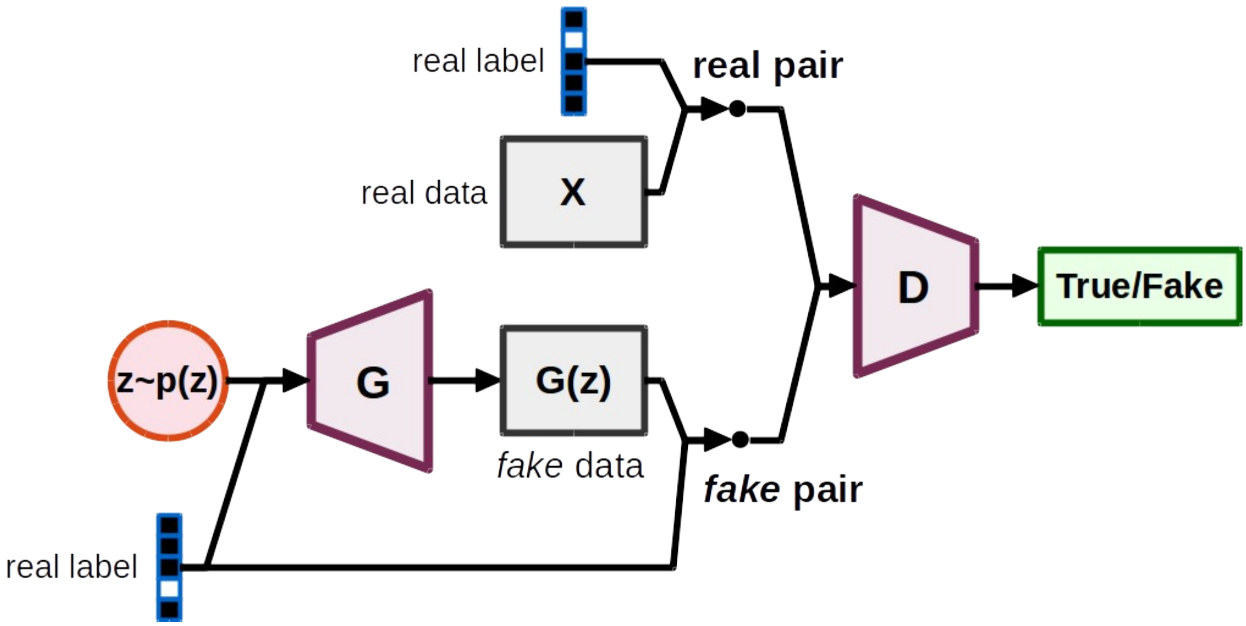
Conditional GANs

Based on the excellent tutorial here.

By formulating the process as a two-player game, Generative Adversarial Networks (GANs) can be very effective in generating realistic content. However, we may want to have more control over what is generated. Conditional GANs offer more control by letting us specify the *class* of output we want. Then we hand the generated content and the class it's supposed to be to the discriminator. The disciminator attempts to differentiate between the generated content of a certain class and the real content of a certain class.

The original paper that described conditional GANs is here.



Libaries

As always, we load lots of libraries.

```
import torch
from torchvision import datasets
import torch.nn as nn
from torch.utils.data import DataLoader
from torchvision import transforms
import numpy as np
import os
from matplotlib.pyplot import imsave
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
```

Data

For this demo, we will be using the MNIST data set. We can apply GANs to other datasets but the training process takes much longer. Our goal will be to supply random noise and a class label (e.g. a digit between 0 and 9) to the generator and produce an image of that particular digit.

```
# A transform to convert the images to tensor and normalize their RGB values
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize(mean=[0.5], std=[0.5])]
)

data = datasets.FashionMNIST(root='../data/', train=True, transform=transform, download=True)

batch_size = 64
data_loader = DataLoader(dataset=data, batch_size=batch_size, shuffle=True, drop_last=True)
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz to ../data/FashionMNIST/raw/train-images-idx3-ubyte.gz

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Extracting ../data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ../data/FashionMNIST/raw

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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz to ../data/FashionMNIST/raw/train-labels-idx1-ubyte.gz

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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to ../data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz


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```

```
Extracting ../data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to
../data/FashionMNIST/raw

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1.amazonaws.com/t10k-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-
1.amazonaws.com/t10k-labels-idx1-ubyte.gz to
../data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz

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Extracting ../data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to
../data/FashionMNIST/raw
```

Helper Functions

We'll need several helper functions for training the conditional GAN. The first converts labels to one hot encoded vectors, we will use it to pass the desired label to the generator. The second will plot a grid of 10x10 images from the generator.

```
def to_onehot(x, num_classes=10):
    assert isinstance(x, int) or isinstance(x, (torch.LongTensor,
torch.cuda.LongTensor))
    if isinstance(x, int):
        c = torch.zeros(1, num_classes).long()
        c[0][x] = 1
    else:
        x = x.cpu()
        c = torch.LongTensor(x.size(0), num_classes)
        c.zero_()
        c.scatter_(1, x, 1) # dim, index, src value
    return c

to_onehot(3)

tensor([[0, 0, 0, 1, 0, 0, 0, 0, 0, 0]])

def get_sample_image(G, DEVICE, n_noise=100):
    img = np.zeros([280, 280])
    for j in range(10):
        c = torch.zeros([10, 10]).to(DEVICE)
        c[:, j] = 1
        z = torch.randn(10, n_noise).to(DEVICE)
        y_hat = G(z,c).view(10, 28, 28)
        result = y_hat.cpu().data.numpy()
        img[j*28:(j+1)*28] = np.concatenate([x for x in result],
```

```
axis=-1)
    return img
```

Architecture

We now instantiate the generator and discriminator architectures. The generator takes a random noise vector and a one hot encoded label as input and produces an image. The discriminator takes an image and a one hot encoded label as input and produces a single value between 0 and 1. The discriminator is trained to output 1 for real images and 0 for fake images. The generator is trained to fool the discriminator by outputting images that look real.

```
class Generator(nn.Module):
    def __init__(self, input_size=100, num_classes=10,
image_size=28*28):
        super(Generator, self).__init__()
        self.network = nn.Sequential(
            nn.Linear(input_size+num_classes, 128), # auxillary
dimension for label
            nn.LeakyReLU(0.2),
            nn.Linear(128, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 512),
            nn.BatchNorm1d(512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 1024),
            nn.BatchNorm1d(1024),
            nn.LeakyReLU(0.2),
            nn.Linear(1024, image_size),
            nn.Tanh()
        )

    def forward(self, x, c):
        x, c = x.view(x.size(0), -1), c.view(c.size(0), -1).float()
        v = torch.cat((x, c), 1) # v: [input, label] concatenated
vector
        y_ = self.network(v)
        y_ = y_.view(x.size(0), 1, 28, 28)
        return y_

class Discriminator(nn.Module):
    def __init__(self, input_size=28*28, num_classes=10,
num_output=1):
        super(Discriminator, self).__init__()
        self.network = nn.Sequential(
            nn.Linear(input_size+num_classes, 512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
```

```
            nn.Linear(256, num_output),
            nn.Sigmoid(),
        )

    def forward(self, x, c):
        x, c = x.view(x.size(0), -1), c.view(c.size(0), -1).float()
        v = torch.cat((x, c), 1) # v: [input, label] concatenated
vector
        y_ = self.network(v)
        return y_
```

Set up and Training

Now, we're ready to instantiate our models, hyperparameters, and optimizers. Since the task is so easy for MNIST, we will train for only 10 epochs. We will update the generator and discriminator in every step but often one can be trained more frequently than the other.

```
MODEL_NAME = 'ConditionalGAN'
DEVICE = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")

D = Discriminator().to(DEVICE) # randomly intialized
G = Generator().to(DEVICE) # randomly initialized

max_epoch = 10
step = 0
n_noise = 100 # size of noise vector

criterion = nn.BCELoss()
D_opt = torch.optim.Adam(D.parameters(), lr=0.0002, betas=(0.5,
0.999))
G_opt = torch.optim.Adam(G.parameters(), lr=0.0002, betas=(0.5,
0.999))

# We will denote real images as 1s and fake images as 0s
# This is why we needed to drop the last batch of the data loader
all_ones = torch.ones([batch_size, 1]).to(DEVICE) # Discriminator
label: real
all_zeros = torch.zeros([batch_size, 1]).to(DEVICE) # Discriminator
Label: fake

images, class_labels = next(iter(data_loader))
class_labels_encoded = class_labels.view(batch_size, 1)
class_labels_encoded = to_onehot(class_labels_encoded).to(DEVICE)
print(class_labels[:10])
print(class_labels_encoded[:10])
```

```
tensor([4, 4, 9, 2, 4, 4, 9, 8, 6, 1])
tensor([[0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
```

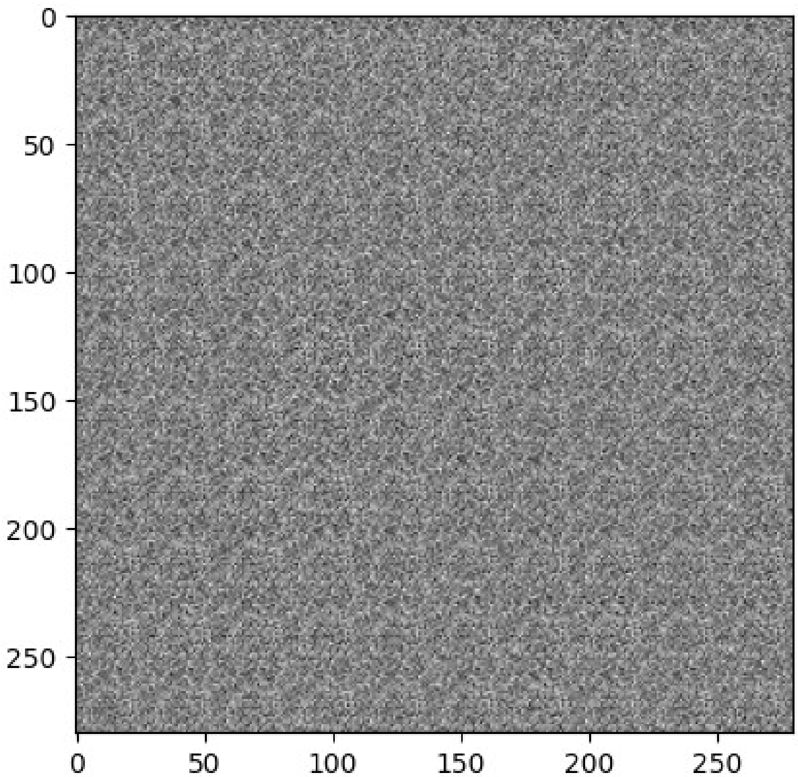
```
        [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
        [0, 0, 1, 0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
        [0, 0, 0, 0, 0, 0, 0, 0, 1, 0],
        [0, 0, 0, 0, 0, 0, 1, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0]], device='cuda:0')

# a directory to save the generated images
if not os.path.exists('samples'):
    os.makedirs('samples')

for epoch in range(max_epoch):
    for idx, (images, class_labels) in enumerate(data_loader):
        # Training Discriminator
        x = images.to(DEVICE)
        class_labels = class_labels.view(batch_size, 1) # add
singleton dimension so batch_size x 1
        class_labels = to_onehot(class_labels).to(DEVICE)
        x_outputs = D(x, class_labels) # input includes labels
        D_x_loss = criterion(x_outputs, all_ones) # Discriminator loss
for real images

        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z, class_labels), class_labels) # input to
both generator and discriminator includes labels
        D_z_loss = criterion(z_outputs, all_zeros) # Discriminator
loss for fake images
        D_loss = D_x_loss + D_z_loss # Total Discriminator loss

        D.zero_grad()
        D_loss.backward()
        D_opt.step()

        # Training Generator
        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z, class_labels), class_labels)
        G_loss = -1 * criterion(z_outputs, all_zeros) # Generator loss
is negative discriminator loss

        G.zero_grad()
        G_loss.backward()
        G_opt.step()

        if step % 500 == 0:
            print('Epoch: {}/{}, Step: {}, D Loss: {}, G Loss:
{}'.format(epoch, max_epoch, step, D_loss.item(), G_loss.item()))
```

```
        if step % 1000 == 0:
            G.eval()
            img = get_sample_image(G, DEVICE, n_noise)
            imsave('samples/{}_step{}.jpg'.format(MODEL_NAME,
str(step).zfill(3)), img, cmap='gray')
            G.train()
        step += 1
```

```
Epoch: 0/10, Step: 0, D Loss: 1.3819940090179443, G Loss: -
0.6990505456924438
Epoch: 0/10, Step: 500, D Loss: 0.9222322106361389, G Loss: -
0.36316925287246704
Epoch: 1/10, Step: 1000, D Loss: 1.306557059288025, G Loss: -
0.30022862553596497
Epoch: 1/10, Step: 1500, D Loss: 1.2047450542449951, G Loss: -
0.4338669180870056
Epoch: 2/10, Step: 2000, D Loss: 1.383216142654419, G Loss: -
0.5744942426681519
Epoch: 2/10, Step: 2500, D Loss: 1.3397421836853027, G Loss: -
0.6760445833206177
Epoch: 3/10, Step: 3000, D Loss: 1.4008440971374512, G Loss: -
0.6481665372848511
Epoch: 3/10, Step: 3500, D Loss: 1.3807786703109741, G Loss: -
0.47795313596725464
Epoch: 4/10, Step: 4000, D Loss: 1.3197503089904785, G Loss: -
0.6316052675247192
Epoch: 4/10, Step: 4500, D Loss: 1.4779423475265503, G Loss: -
0.6468305587768555
Epoch: 5/10, Step: 5000, D Loss: 1.3649685382843018, G Loss: -
0.722814679145813
Epoch: 5/10, Step: 5500, D Loss: 1.3152425289154053, G Loss: -
0.6868982315063477
Epoch: 6/10, Step: 6000, D Loss: 1.318251609802246, G Loss: -
0.7387551665306091
Epoch: 6/10, Step: 6500, D Loss: 1.2910850048065186, G Loss: -
0.5901193022727966
Epoch: 7/10, Step: 7000, D Loss: 1.3347728252410889, G Loss: -
0.6987571120262146
Epoch: 8/10, Step: 7500, D Loss: 1.4143143892288208, G Loss: -
0.6107622385025024
Epoch: 8/10, Step: 8000, D Loss: 1.3565864562988281, G Loss: -
0.6859310865402222
Epoch: 9/10, Step: 8500, D Loss: 1.3550758361816406, G Loss: -
0.640485942363739
Epoch: 9/10, Step: 9000, D Loss: 1.3872662782669067, G Loss: -
0.6289292573928833
```

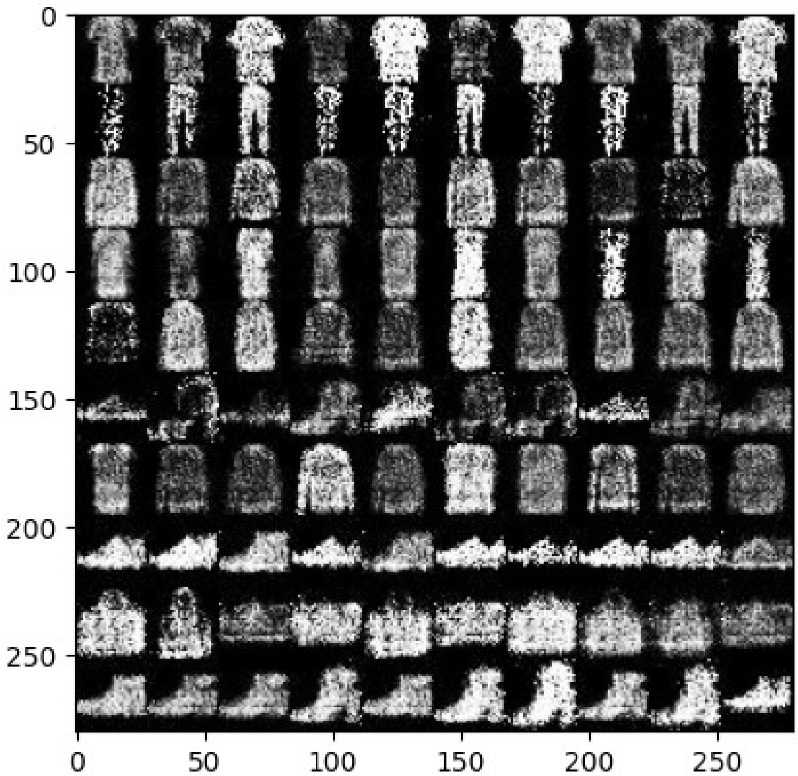
Now let's plot these images. At first, the generator just produces noise (as we expect).

```
img = mpimg.imread('samples/ConditionalGAN_step000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



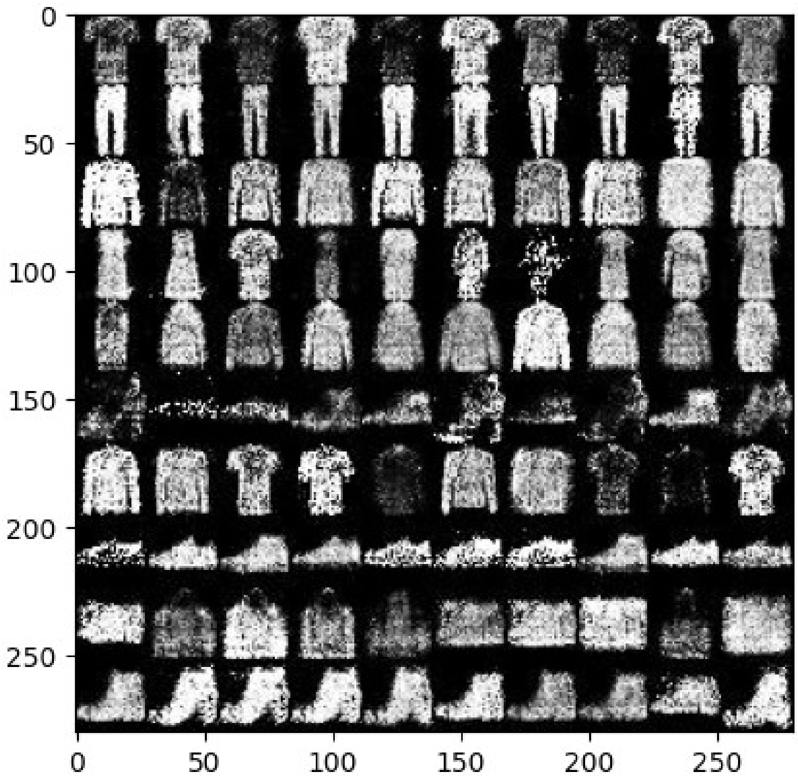
But then it gets better.

```
img = mpimg.imread('samples/ConditionalGAN_step5000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



In fact, if we don't look too closely, we can recognize the numbers it produces.

```
img = mpimg.imread('samples/ConditionalGAN_step9000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



And by the time we're done training, even the worst images look like messy handwriting!