# Feed-Forward Neural Networks, Autoencoders, and Generative Models

## 1 Introduction

In this assignment, we first use simple supervised networks to classify handwritten digits, and will then apply these techniques to generate novel images of digits using Variational Autoencoders and GANs. Afterwards, we will apply information theoretic measures to assess the success of the generative models.

## 2 MNIST Classification

```
import torch
import torchvision.datasets as datasets
import torchvision.transforms as transforms
import matplotlib.pyplot as plt

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

### 2.1 Downloading MNIST

```
mnist_train = datasets.MNIST(root = 'data', train=True, download=True, trans
mnist_test = datasets.MNIST(root = 'data', train=False, download=True,transf
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to
```

9920512/? [00:20<00:00, 41882769.81it/s]

```
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to
```

32768/? [00:00<00:00, 400862.61it/s]

```
Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to d
```

1654784/? [00:19<00:00, 141342.26it/s]

```
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to d
```

8192/? [00:00<00:00, 28643.81it/s]

```
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
Processing...
Done!
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:480: U
  return torch.from_numpy(parsed.astype(m[2], copy=False)).view(*s)
```

```
def evaluate(model, evaluation_set, loss_fn):
    """
    Evaluates the given model on the given dataset.
    Returns the percentage of correct classifications out of total classific
    """
    with torch.no_grad(): # this disables backpropogation, which makes the m
        # TODO: Fill in the rest of the evaluation function.
        losses = []
        sum_total = 0
        for data, targets in evaluation_set:
          data = data.to(device)
          targets = targets.to(device)
          model_input = data.view(-1, 784)
          out = model(model_input)
          arg_maxed = torch.argmax(out, dim = 1)

          sum_total += (arg_maxed == targets).float().sum()
          losses.append(loss_fn(out, targets).item())
        loss = sum(losses) / len(losses)
        accuracy =  100 * sum_total / len(evaluation_set.dataset)
    return accuracy, loss

def train(model,loss_fn, optimizer, train_loader, test_loader):
```

```
    """
    This is a standard training loop, which leaves some parts to be filled i
    INPUT:
    :param model: an untrained pytorch model
    :param loss_fn: e.g. Cross Entropy loss of Mean Squared Error.
    :param optimizer: the model optimizer, initialized with a learning rate.
    :param training_set: The training data, in a dataloader for easy iterati
    :param test_loader: The testing data, in a dataloader for easy iteratior
    """
    num_epochs = 100 # obviously, this is too many. I don't know what this a
    train_loss = []
    train_acc = []
    test_loss = []
    test_acc = []
    for epoch in range(num_epochs):
        # loop through each data point in the training set
        for data, targets in train_loader:
            data = data.to(device)
            targets = targets.to(device)
            optimizer.zero_grad()

            # run the model on the data
            model_input = data.view(-1, 784)# TODO: Turn the 28 by 28 image
            out = model(model_input)

            # Calculate the loss
            loss = loss_fn(out,targets)

            # Find the gradients of our loss via backpropogation
            loss.backward()

            # Adjust accordingly with the optimizer
            optimizer.step()

        # Give status reports every 100 epochs
        if epoch % 100==0:
            print(f" EPOCH {epoch}. Progress: {epoch/num_epochs*100}%. ")
            tr_acc, tr_loss = evaluate(model, train_loader, loss_fn)
            te_acc, te_loss = evaluate(model, test_loader, loss_fn)
            train_loss.append(tr_loss)
            train_acc.append(tr_acc)
            test_loss.append(te_loss)
            test_acc.append(te_acc)


            print(f" Train accuracy: {tr_acc}. Test accuracy: {te_acc}") #T(

    return train_loss, train_acc, test_loss, test_acc
```

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## 2.2 Logistic Regression

> First, we will explore implementing a simple model that can take in images of handwritten digits and classify them from 0 to 9. We will do this using a multinomial logistic regression model trained with gradient descent。

```
from torch.nn.functional import softmax
import torch.nn.functional as F
from torch import optim, nn
import torchvision.transforms as transforms
import torchvision.datasets as datasets
import numpy as np
import torch
```

```
class LogisticRegression(nn.Module): # initialize a pytorch neural network m
    def __init__(self): # initialize the model
        super(LogisticRegression, self).__init__() # call for the parent cla
        # you can define variables here that apply to the entire model (e.g.
        # this model only has two parameters: the weight, and the bias.
        # here's how you can initialize the weight:
        # W = nn.Parameter(torch.zeros(shape)) # this creates a model parame
        # ... torch.zeros is much like numpy.zeros, except optimized for bac

        # create a bias variable here
        self.W = nn.Parameter(torch.zeros((784, 10)), requires_grad = True)
        self.b = nn.Parameter(torch.zeros((1, 10)), requires_grad = True)


    def forward(self, x):
        """
        this is the function that will be executed when we call the logistic
        INPUT:
            x, an MNIST image represented as a tensor of shape 784
        OUTPUT:
            predictions, a tensor of shape 10. If using CrossEntropyLoss, yo
        """
        # put the logic here.
        predictions = torch.matmul(x, self.W) + self.b
        predictions = softmax(predictions)

        return predictions
```

```
model = LogisticRegression().to(device)
# initialize the optimizer, and set the learning rate
SGD = torch.optim.SGD(model.parameters(), lr = 5e-1)
# initialize the loss function. You don't want to use this one, so change it
loss_fn = torch.nn.CrossEntropyLoss()
batch_size = 128
train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,
train_loss, train_acc, test_loss, test_acc = train(model = model,loss_fn = l
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:25: UserWarnin
 EPOCH 0. Progress: 0.0%.
 Train accuracy: 87.461669921875. Test accuracy: 88.30999755859375
 EPOCH 100. Progress: 66.66666666666666%.
 Train accuracy: 93.94667053222656. Test accuracy: 92.94999694824219
```

Question 2.2.1. What percentage classification accuracy did your simple network achieve?

~91%

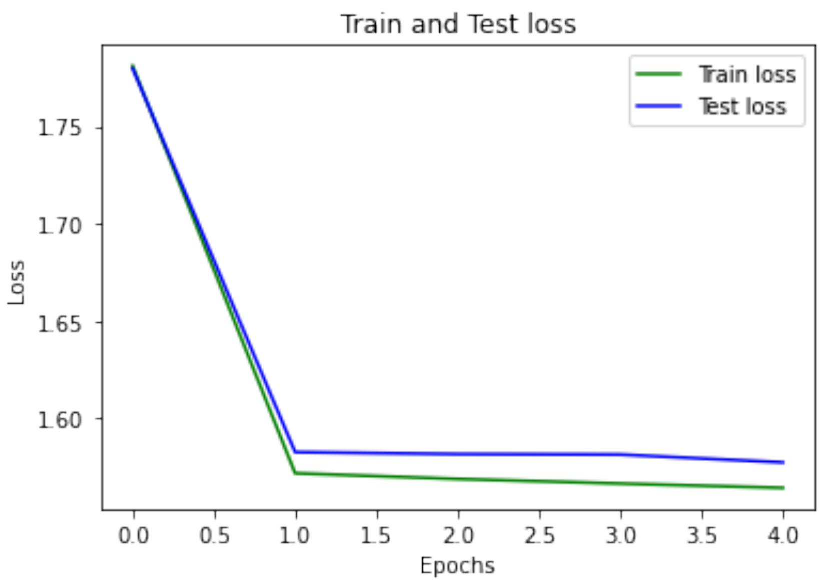
## 2.3 Feed-forward Neural Network

```
class FeedForwardNet(nn.Module):
    """ Simple feed forward network with one hidden layer."""
    # Here, you should place an exact copy of the code from the LogisticRegr
    # 1. Add another weight and bias vector to represent the hidden layer
    # 2. In the forward function, add some type of nonlinearity to the outpu
    def __init__(self):
      super(FeedForwardNet, self).__init__()
      self.W1 = nn.Parameter(torch.randn((784, 128)), requires_grad = True)
      self.b1 = nn.Parameter(torch.zeros((1, 128)), requires_grad = True)
      self.W2 = nn.Parameter(torch.randn((128, 10)), requires_grad = True)
      self.b2 = nn.Parameter(torch.zeros((1, 10)), requires_grad = True)

    def forward(self, x):
      predictions = torch.matmul(x, self.W1) + self.b1
      predictions = F.relu(predictions)
      predictions = torch.matmul(predictions, self.W2) + self.b2
      predictions = softmax(predictions)
      return predictions
```

```
model = FeedForwardNet().to(device)
# initialize the optimizer, and set the learning rate
adam = torch.optim.Adam(model.parameters(), lr = 3e-3) # This is absurdly hi
# initialize the loss function. You don't want to use this one, so change it
loss_fn = torch.nn.CrossEntropyLoss()
batch_size = 128
train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,
train_loss, train_acc, test_loss, test_acc = train(model = model,loss_fn = l
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:17: UserWarnin
 EPOCH 0. Progress: 0.0%.
 Train accuracy: 67.92500305175781. Test accuracy: 68.18999481201172
 EPOCH 100. Progress: 20.0%.
 Train accuracy: 88.91166687011719. Test accuracy: 87.9000015258789
 EPOCH 200. Progress: 40.0%.
 Train accuracy: 89.20833587646484. Test accuracy: 87.94999694824219
 EPOCH 300. Progress: 60.0%.
 Train accuracy: 89.44667053222656. Test accuracy: 88.04000091552734
 EPOCH 400. Progress: 80.0%.
 Train accuracy: 89.66666412353516. Test accuracy: 88.29999542236328
```

```
epochs = range(0,len(train_loss))
plt.plot(epochs, train_loss, 'g', label='Train loss')
plt.plot(epochs, test_loss, 'b', label='Test loss')
plt.title('Train and Test loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
from sklearn.metrics import confusion_matrix as conf_mat
labels = []
outs = []
with torch.no_grad():
  for i, (inputs, classes) in enumerate(test_loader):
    inputs = inputs.to(device)
    classes = classes.to(device)
    outputs = model(inputs.view(-1, 784))
    preds = torch.argmax(outputs, 1)
    labels.extend(classes.detach().cpu().numpy())
    outs.extend(preds.detach().cpu().numpy())

conf_mat(labels, outs)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:17: UserWarnin
array([[ 973,    0,    1,    1,    0,    0,    1,    2,    2,    0],
       [   0, 1123,    3,    1,    0,    0,    5,    1,    2,    0],
       [   2,    2, 1006,    6,    1,    0,    4,    6,    5,    0],
       [   0,    0,    6,  980,    0,   13,    0,    3,    8,    0],
       [   1,    1,    2,    0,  972,    0,    6,    0,    0,    0],
       [   4,    0,    0,    7,    3,  861,    9,    1,    7,    0],
       [   3,    1,    1,    1,    1,    2,  946,    0,    3,    0],
       [   1,    5,    8,    1,    1,    1,    0, 1006,    5,    0],
       [   5,    1,    1,    4,    1,    0,    2,    5,  955,    0],
       [  13,   11,    3,  108,  595,   69,    0,  105,  105,    0]])
```

Question 2.3.1. What percentage classification accuracy does this more complex network achieve?

89%

Question 2.3.2. Create a plot of the training and test error vs the number of iterations. How many iterations are sufficient to reach good performance?

around 150 epochs seems to be sufficient

Question 2.3.3. Print the confusion matrix showing which digits were misclassified, and what they were misclassified as. What numbers are frequently confused with one another by your model?

For some reason there seems to be a problem with the 9 digit. It was never classifier correctly and it is often misclassified with the 4 digit.

Question 2.3.4. Experiment with the learning rate, optimizer and activation function of your network. Report the best accuracy and briefly describe the training scheme that reached this accuracy.

Using relu activation functions with an Adam optimizer this accuracy was achieved. It worked best with 1e-3 learning rate. I tried with various learning rates and it seemed Adam with this learning rate worked best

# 3 Autoencoder

```
class Autoencoder(nn.Module):
    def __init__(self):
        super(Autoencoder, self).__init__()
        self.enc_lin1 = nn.Linear(784, 1000)
        self.enc_lin2 = nn.Linear(1000, 500)
        self.enc_lin3 = nn.Linear(500, 250)
        self.enc_lin4 = nn.Linear(250, 2)

        self.dec_lin1 = nn.Linear(2, 250)
        self.dec_lin2 = nn.Linear(250, 500)
        self.dec_lin3 = nn.Linear(500, 1000)
        self.dec_lin4 = nn.Linear(1000, 784)


    def encode(self, x):
        x = F.tanh(self.enc_lin1(x))
        x = F.tanh(self.enc_lin2(x))
        x = F.tanh(self.enc_lin3(x))
        x = self.enc_lin4(x)

        # ... additional layers, plus possible nonlinearities.
        return x

    def decode(self, z):
        # ditto, but in reverse
        z = F.tanh(self.dec_lin1(z))
        z = F.tanh(self.dec_lin2(z))
        z = F.tanh(self.dec_lin3(z))
        z = F.sigmoid(self.dec_lin4(z))

        return z

    def forward(self, x):
        z = self.encode(x)
        return self.decode(z)

```

```
import matplotlib.pyplot as plt

def evaluate_ae(model, evaluation_set, loss_fn):
    """
    Evaluates the given model on the given dataset.
    Returns the percentage of correct classifications out of total classific
    """
    with torch.no_grad(): # this disables backpropogation, which makes the m
        # TODO: Fill in the rest of the evaluation function.
        losses = []
```

```
        sum_total = 0
        for ind, (data, targets) in enumerate(evaluation_set):
          data = data.to(device)
          model_input = data.view(-1, 784)
          out = model(model_input)
          # if ind == 0:
          #   visualise_output(model_input, model)
          sum_total += (out == model_input).float().sum()
          losses.append(loss_fn(out, model_input).item())
        loss = sum(losses) / len(losses)
        accuracy =  100 * sum_total / len(evaluation_set.dataset)
    return accuracy, loss

def train_ae(model,loss_fn, optimizer, train_loader, test_loader):
    """
    This is a standard training loop, which leaves some parts to be filled i
    INPUT:
    :param model: an untrained pytorch model
    :param loss_fn: e.g. Cross Entropy loss of Mean Squared Error.
    :param optimizer: the model optimizer, initialized with a learning rate.
    :param training_set: The training data, in a dataloader for easy iterati
    :param test_loader: The testing data, in a dataloader for easy iteratior
    """
    num_epochs = 500 # obviously, this is too many. I don't know what this a
    train_loss = []
    train_acc = []
    test_loss = []
    test_acc = []

    to_graph = {}
    while True:
      for data, targets in test_loader:
        for d, t in zip(data, targets):
          if int(t) not in to_graph.keys():
            to_graph[int(t)] = d
          if len(to_graph) == 10:
            break
        if len(to_graph) == 10:
            break
      if len(to_graph) == 10:
            break

    for epoch in range(num_epochs):
        # loop through each data point in the training set
        for data, targets in train_loader:
            optimizer.zero_grad()
            data = data.to(device)
            # run the model on the data
```

```
            model_input = data.view(-1, 784)# TODO: Turn the 28 by 28 image
            out = model(model_input)

            # Calculate the loss
            loss = loss_fn(out, model_input)

            # Find the gradients of our loss via backpropogation
            loss.backward()

            # Adjust accordingly with the optimizer
            optimizer.step()

        # Give status reports every 100 epochs
        if epoch % 100==0:
            print(f" EPOCH {epoch}. Progress: {epoch/num_epochs*100}%. ")
            tr_acc, tr_loss = evaluate_ae(model, train_loader, loss_fn)
            te_acc, te_loss = evaluate_ae(model, test_loader, loss_fn)
            train_loss.append(tr_loss)
            train_acc.append(tr_acc)
            test_loss.append(te_loss)
            test_acc.append(te_acc)



            # im = next(iter(train_loader))[0][0]
            # plt.imshow(im.squeeze())
            # plt.show()
            # # import pdb; pdb.set_trace()

            # with torch.no_grad():
            #   plt.imshow(torch.reshape(model(im.view(-1, 784)), (28,28)).r
            #   plt.show()


            print(f" Train Loss: {tr_loss}. Test Loss: {te_loss}") #TODO: in

    for label, data in to_graph.items():
      plt.imshow(data.squeeze())
      plt.show()
      with torch.no_grad():
        plt.imshow(torch.reshape(model(data.view(-1, 784)), (28,28)).numpy()
        plt.show()
    return train_loss, train_acc, test_loss, test_acc
```

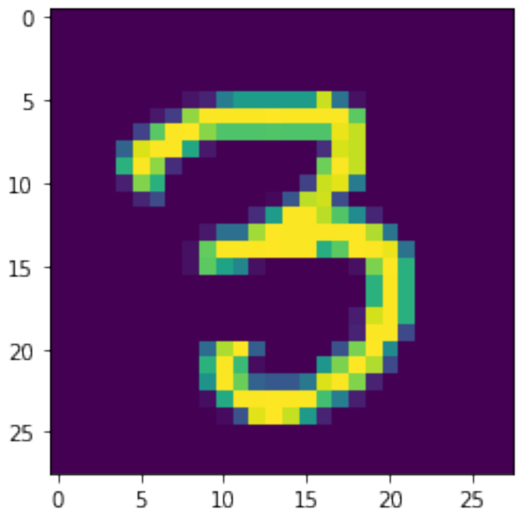
# 3.1 MNIST

```
model = Autoencoder().to(device)
# initialize the optimizer, and set the learning rate
optimizer = torch.optim.Adam(model.parameters(), lr = 0.003) # This is absur
# initialize the loss function. You don't want to use this one, so change it
loss_fn = torch.nn.MSELoss()
batch_size = 128
train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,
train_ae(model = model,loss_fn = loss_fn, optimizer = optimizer, train_loade
```

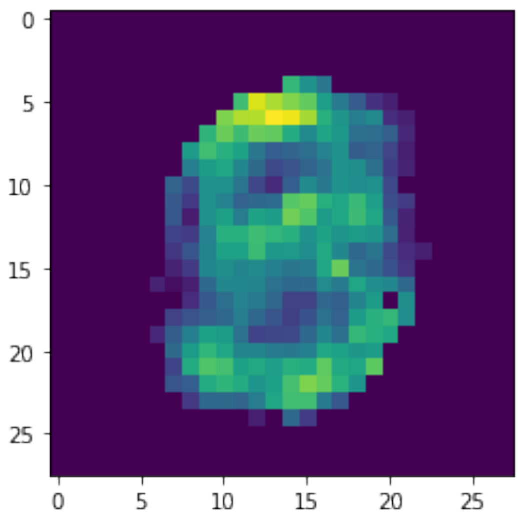
```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1628: UserWar
  warnings.warn("nn.functional.tanh is deprecated. Use torch.tanh instead."
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1639: UserWar
  warnings.warn("nn.functional.sigmoid is deprecated. Use torch.sigmoid ins
 EPOCH 0. Progress: 0.0%.
 Train Loss: 0.04769748952120606. Test Loss: 0.047753466222482395
 EPOCH 100. Progress: 20.0%.
 EPOCH 200. Progress: 40.0%.
 Train Loss: 0.046536173179014914. Test Loss: 0.04638722930339318
 EPOCH 300. Progress: 60.0%.
 Train Loss: 0.051131408375654136. Test Loss: 0.05109376780971696
 EPOCH 400. Progress: 80.0%.
 Train Loss: 0.0534530708641767. Test Loss: 0.05327377793721006
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-8-5c402a189ed2> in <module>()
      7 train_loader = torch.utils.data.DataLoader(mnist_train,
batch_size=batch_size, shuffle=True)
      8 test_loader = torch.utils.data.DataLoader(mnist_test,
batch_size=batch_size, shuffle=True)
----> 9 train_ae(model = model,loss_fn = loss_fn, optimizer = optimizer,
train_loader = train_loader, test_loader = test_loader)

<ipython-input-7-fe3d57a57411> in train_ae(model, loss_fn, optimizer,
train_loader, test_loader)
     92
     93     for label, data in to_graph.items():
---> 94       plt.imshow(data.squeeze())
     95       plt.show()
     96       with torch.no_grad():
```

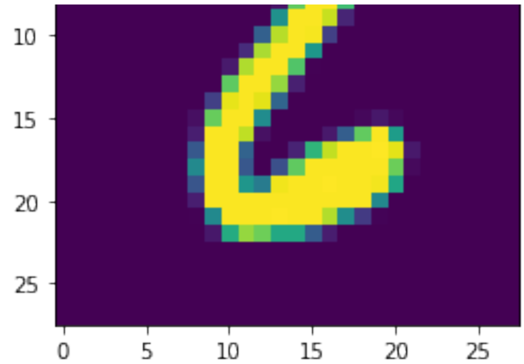
```
import matplotlib.pyplot as plt

to_graph = {}
while True:
  for data, targets in train_loader:
    for d, t in zip(data, targets):
      if int(t) not in to_graph.keys():
        to_graph[int(t)] = d
```

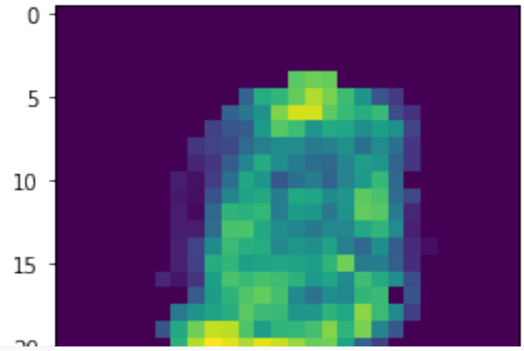
```
          if len(to_graph) == 10:
            break
        if len(to_graph) == 10:
            break
      if len(to_graph) == 10:
            break

    for label, data in to_graph.items():
      plt.imshow(data.squeeze())
      plt.show()
      with torch.no_grad():
        data = data.to(device)
        plt.imshow(torch.reshape(model(data.view(-1, 784)), (28,28)).cpu().numpy
        plt.show()
```




```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1628: UserWa
  warnings.warn("nn.functional.tanh is deprecated. Use torch.tanh instead
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1639: UserWa
  warnings.warn("nn.functional.sigmoid is deprecated. Use torch.sigmoid in
```



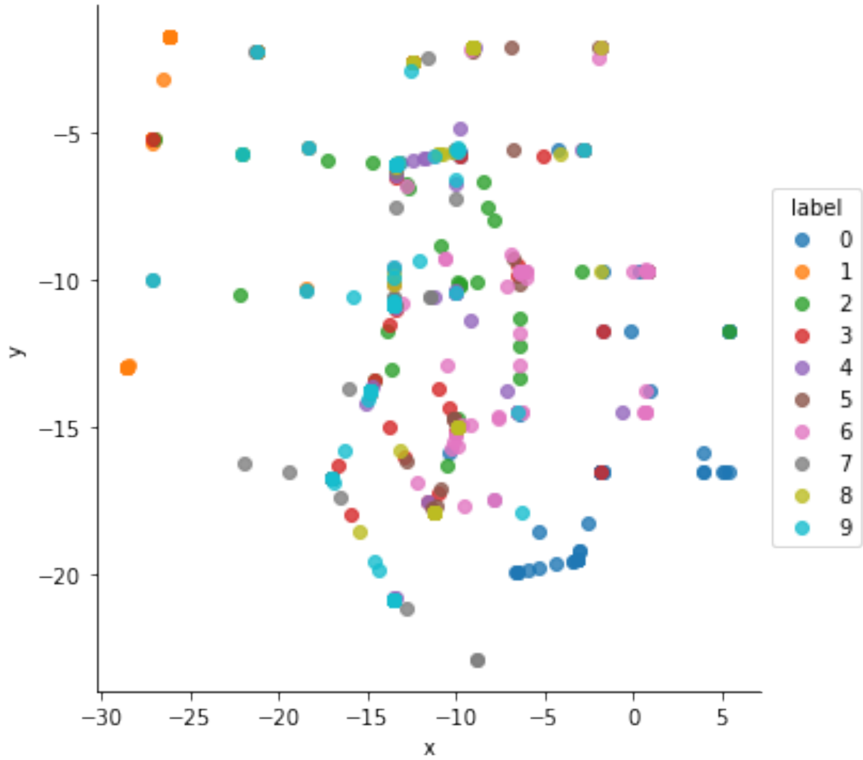





```
1 import seaborn as sns
2 import pandas as pd
3 import matplotlib.pyplot as plt
```

```
thousand_loader = torch.utils.data.DataLoader(mnist_train, batch_size = 100(
for data, target in thousand_loader:
  with torch.no_grad():
    data = data.to(device)
    model_input = data.view(-1, 784)# TODO: Turn the 28 by 28 image tensors
    out = model.encode(model_input).detach().cpu().numpy()
    labels = target
    break

df = {'x': out[:, 0], 'y': out[:, 1], 'label': labels.numpy()}



data = pd.DataFrame(df)
facet = sns.lmplot(data=data, x='x', y='y', hue='label',
                   fit_reg=False, legend=False)

#add a legend
leg = facet.ax.legend(bbox_to_anchor=[1, 0.75],
                      title="label", fancybox=True)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1628: UserWar
  warnings.warn("nn.functional.tanh is deprecated. Use torch.tanh instead."
```



Question 3.1.1. Do the colors easily separate, or are they all clumped together? Which numbers are frequently embedded close together, and what does this mean?

The colors easily separate, but it does not seem like there are any distinct custers. Perhaps with optimized training there would be. The 1s and 0s seem to be pretty dictinct, but something like an 8 which has many lines, seems to be scattered throughout. It also seems like 2s and 6s are somewhat close, which means the network learned these embeddings to have similar values.

Question 3.1.2. How realistic were the images you generated by interpolating between points in the latent space? Can you think of a better way to generate images with an autoencoder?

The generated images were not too realistic. Perhaps with more dimensions between the encoder and decoder, we could see better results.

## 3.2 Biological Data: Retinal Bipolar Dataset

```
import pickle
with open('retinal-bipolar-data.pickle', 'rb') as f:
  retinal = pickle.load(f)
with open('retinal-bipolar-metadata.pickle', 'rb') as f:
  retinal_meta = pickle.load(f)
```

```
retinal.shape
```

```
(21552, 15524)
```

```
msk = np.random.rand(len(retinal)) < 0.8

ret_train = torch.Tensor(retinal[msk].values.astype(np.float32))
ret_tr_y = torch.Tensor(retinal_meta[msk]['CLUSTER'].values.astype(np.float3
ret_test = torch.Tensor(retinal[~msk].values.astype(np.float32))
ret_te_y = torch.Tensor(retinal_meta[~msk]['CLUSTER'].values.astype(np.float
```

```
ret_train = torch.utils.data.TensorDataset(ret_train, ret_tr_y)
ret_test = torch.utils.data.TensorDataset(ret_test, ret_te_y)
```

```
class Ret_Autoencoder(Autoencoder):
  def __init__(self, input_size):
    super(Autoencoder, self).__init__()
    self.enc_lin1 = nn.Linear(input_size, 1000)
    self.enc_lin2 = nn.Linear(1000, 500)
    self.enc_lin3 = nn.Linear(500, 250)
    self.enc_lin4 = nn.Linear(250, 2)

    self.dec_lin1 = nn.Linear(2, 250)
    self.dec_lin2 = nn.Linear(250, 500)
    self.dec_lin3 = nn.Linear(500, 1000)
    self.dec_lin4 = nn.Linear(1000, input_size)

  def decode(self, z):
    # ditto, but in reverse
    z = F.tanh(self.dec_lin1(z))
    z = F.tanh(self.dec_lin2(z))
    z = F.tanh(self.dec_lin3(z))
    z = self.dec_lin4(z)

    return z

```

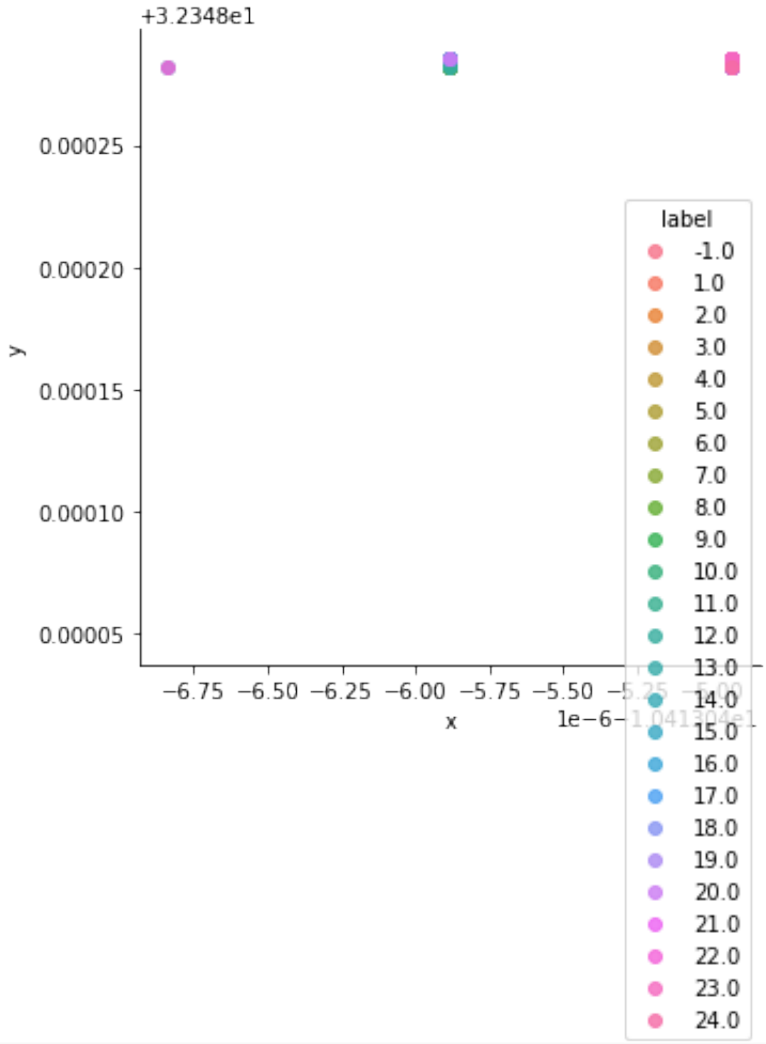
```
import matplotlib.pyplot as plt

def evaluate_ret_ae(model, evaluation_set, loss_fn):
    """
    Evaluates the given model on the given dataset.
    Returns the percentage of correct classifications out of total classific
    """
    with torch.no_grad(): # this disables backpropogation, which makes the m
        # TODO: Fill in the rest of the evaluation function.
        losses = []
        sum_total = 0
        for ind, (data, targets) in enumerate(evaluation_set):
          data = data.to(device)
          model_input = data
          out = model(model_input)
          # if ind == 0:
          #   visualise_output(model_input, model)
          sum_total += (out == model_input).float().sum()
          losses.append(loss_fn(out, model_input).item())
        loss = sum(losses) / len(losses)
        accuracy =  100 * sum_total / len(evaluation_set.dataset)
    return accuracy, loss

def train_ret_ae(model,loss_fn, optimizer, train_loader, test_loader):
```

```
    """
    This is a standard training loop, which leaves some parts to be filled i
    INPUT:
    :param model: an untrained pytorch model
    :param loss_fn: e.g. Cross Entropy loss of Mean Squared Error.
    :param optimizer: the model optimizer, initialized with a learning rate.
    :param training_set: The training data, in a dataloader for easy iterati
    :param test_loader: The testing data, in a dataloader for easy iteratior
    """
    num_epochs = 500 # obviously, this is too many. I don't know what this a
    train_loss = []
    train_acc = []
    test_loss = []
    test_acc = []

    for epoch in range(num_epochs):
        # loop through each data point in the training set
        for data, targets in train_loader:
            optimizer.zero_grad()
            data = data.to(device)
            # run the model on the data
            model_input = data
            out = model(model_input)

            # Calculate the loss
            loss = loss_fn(out, model_input)

            # Find the gradients of our loss via backpropogation
            loss.backward()

            # Adjust accordingly with the optimizer
            optimizer.step()

        # Give status reports every 100 epochs
        if epoch % 100==0:
            print(f" EPOCH {epoch}. Progress: {epoch/num_epochs*100}%. ")
            tr_acc, tr_loss = evaluate_ret_ae(model, train_loader, loss_fn)
            te_acc, te_loss = evaluate_ret_ae(model, test_loader, loss_fn)
            train_loss.append(tr_loss)
            train_acc.append(tr_acc)
            test_loss.append(te_loss)
            test_acc.append(te_acc)

            print(f" Train Loss: {tr_loss}. Test Loss: {te_loss}") #TODO: in

    return train_loss, train_acc, test_loss, test_acc
```

```
model = Ret_Autoencoder(input_size = 15524).to(device)
# initialize the optimizer, and set the learning rate
optimizer = torch.optim.Adam(model.parameters(), lr = 0.003) # This is absur
# initialize the loss function. You don't want to use this one, so change it
loss_fn = torch.nn.MSELoss()
batch_size = 128
train_loader = torch.utils.data.DataLoader(ret_train, batch_size=batch_size,
test_loader = torch.utils.data.DataLoader(ret_test, batch_size=batch_size, s
train_ret_ae(model = model,loss_fn = loss_fn, optimizer = optimizer, train_l
```

```
thousand_loader = torch.utils.data.DataLoader(ret_test, batch_size = 1000, s
for data, target in thousand_loader:
  with torch.no_grad():
    data = data.to(device)
    model_input = data
    out = model.encode(model_input).detach().cpu().numpy()
    labels = target
    break

df = {'x': out[:, 0], 'y': out[:, 1], 'label': labels.numpy()}



data = pd.DataFrame(df)
facet = sns.lmplot(data=data, x='x', y='y', hue='label',
                   fit_reg=False, legend=False)

#add a legend
leg = facet.ax.legend(bbox_to_anchor=[1, 0.75],
                         title="label", fancybox=True)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1628: UserWar
  warnings.warn("nn.functional.tanh is deprecated. Use torch.tanh instead."
```




Question 3.2.1. How many clusters are visible in the embedding? Do they correspond to the cluster labels?

It seems like there was only three clusters. The y dimension seems to have very little variance. It does seem, however, that there is a trend, where numbers found the same x value and ended up in three different bins.

# 4 Generative Models

## 4.1 The Variational Autoencoder

```
##### vae.py

import torch
import torch.utils.data
from torch import nn, optim
from torch.nn import functional as F
from torchvision import datasets, transforms
from torchvision.utils import save_image

train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,

batch_size = 128
epochs = 10
seed = 1
log_interval = 10


class VAE(nn.Module):
    def __init__(self):
        super(VAE, self).__init__()

        self.fc1 = nn.Linear(784, 400)
        self.fc21 = nn.Linear(400, 20)
        self.fc22 = nn.Linear(400, 20)
        self.fc3 = nn.Linear(20, 400)
        self.fc4 = nn.Linear(400, 784)

    def encode(self, x):
        h1 = F.relu(self.fc1(x))
        return self.fc21(h1), self.fc22(h1)

    def reparameterize(self, mu, logvar):
        std = torch.exp(0.5*logvar)
        eps = torch.randn_like(std)
        return mu + eps*std

    def decode(self, z):
        h3 = F.relu(self.fc3(z))
        return torch.sigmoid(self.fc4(h3))

    def forward(self, x):
        mu, logvar = self.encode(x.view(-1, 784))
        z = self.reparameterize(mu, logvar)
        return self.decode(z), mu, logvar
```

```


def VAE_loss_function(recon_x, x, mu, logvar):
    # TO DO: Implement reconstruction + KL divergence losses summed over all

    # see lecture 12 slides for more information on the VAE loss function
    # for additional information on computing KL divergence
    # see Appendix B from VAE paper:
    # Kingma and Welling. Auto-Encoding Variational Bayes. ICLR, 2014
    # https://arxiv.org/abs/1312.6114

    # x = x.squeeze(1)
    recon_loss = F.binary_cross_entropy(recon_x, x.view(-1, 784), reduction=
    KLD = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
    return recon_loss + KLD


def train(epoch):
    model.train()
    train_loss = 0
    for batch_idx, (data, _) in enumerate(train_loader):
        data = data.to(device)
        optimizer.zero_grad()
        recon_batch, mu, logvar = model(data)
        loss = VAE_loss_function(recon_batch, data, mu, logvar)
        loss.backward()
        train_loss += loss.item()
        optimizer.step()
        if batch_idx % log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader),
                loss.item() / len(data)))

    print('====> Epoch: {} Average loss: {:.4f}'.format(
          epoch, train_loss / len(train_loader.dataset)))


def test(epoch):
    model.eval()
    test_loss = 0
    with torch.no_grad():
        for i, (data, _) in enumerate(test_loader):
            data = data.to(device)
            recon_batch, mu, logvar = model(data)
            test_loss += VAE_loss_function(recon_batch, data, mu, logvar).it
            if i == 0:
                n = min(data.size(0), 8)
```

```
                comparison = torch.cat([data[:n],
                                      recon_batch.view(batch_size, 1, 28, 28
                save_image(comparison.cpu(),
                         'results/reconstruction_' + str(epoch) + '.png', nr

    test_loss /= len(test_loader.dataset)
    print('====> Test set loss: {:.4f}'.format(test_loss))



```

```
!mkdir results
```

```
#if name = main
train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = VAE().to(device)
optimizer = optim.Adam(model.parameters(), lr=1e-3)
for epoch in range(1, epochs + 1):
    train(epoch)
    test(epoch)
    with torch.no_grad():
        sample = torch.randn(64, 20).to(device)
        sample = model.decode(sample).cpu()
        save_image(sample.view(64, 1, 28, 28),
                   'results/sample_' + str(epoch) + '.png')
```

```
Train Epoch: 1 [0/60000 (0%)]	Loss: 547.250000
Train Epoch: 1 [1280/60000 (2%)]	Loss: 304.746094
Train Epoch: 1 [2560/60000 (4%)]	Loss: 233.603378
Train Epoch: 1 [3840/60000 (6%)]	Loss: 221.929214
Train Epoch: 1 [5120/60000 (9%)]	Loss: 218.519470
Train Epoch: 1 [6400/60000 (11%)]	Loss: 215.135056
Train Epoch: 1 [7680/60000 (13%)]	Loss: 207.176376
Train Epoch: 1 [8960/60000 (15%)]	Loss: 203.229523
Train Epoch: 1 [10240/60000 (17%)]	Loss: 188.281433
Train Epoch: 1 [11520/60000 (19%)]	Loss: 188.851898
Train Epoch: 1 [12800/60000 (21%)]	Loss: 182.265137
Train Epoch: 1 [14080/60000 (23%)]	Loss: 179.018768
Train Epoch: 1 [15360/60000 (26%)]	Loss: 177.512329
Train Epoch: 1 [16640/60000 (28%)]	Loss: 162.004517
Train Epoch: 1 [17920/60000 (30%)]	Loss: 162.069183
Train Epoch: 1 [19200/60000 (32%)]	Loss: 163.561600
Train Epoch: 1 [20480/60000 (34%)]	Loss: 155.700745
Train Epoch: 1 [21760/60000 (36%)]	Loss: 158.180450
Train Epoch: 1 [23040/60000 (38%)]	Loss: 162.674438
Train Epoch: 1 [24320/60000 (41%)]	Loss: 154.532822
Train Epoch: 1 [25600/60000 (43%)]	Loss: 153.583633
Train Epoch: 1 [26880/60000 (45%)]	Loss: 154.731003
```

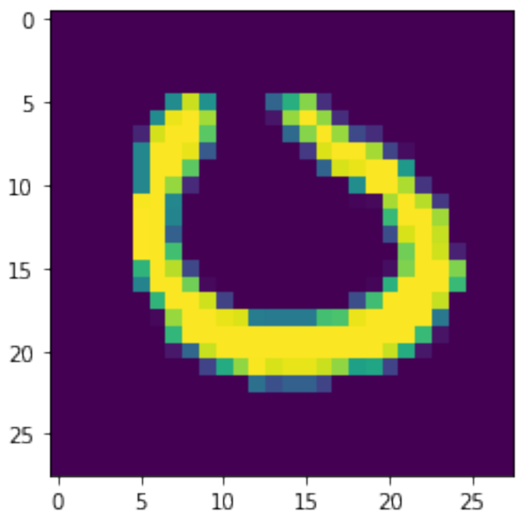
```
Train Epoch: 1 [28160/60000 (47%)]	Loss: 149.200836
Train Epoch: 1 [29440/60000 (49%)]	Loss: 150.456726
Train Epoch: 1 [30720/60000 (51%)]	Loss: 146.824585
Train Epoch: 1 [32000/60000 (53%)]	Loss: 143.879807
Train Epoch: 1 [33280/60000 (55%)]	Loss: 152.822159
Train Epoch: 1 [34560/60000 (58%)]	Loss: 143.549591
Train Epoch: 1 [35840/60000 (60%)]	Loss: 141.609024
Train Epoch: 1 [37120/60000 (62%)]	Loss: 142.283875
Train Epoch: 1 [38400/60000 (64%)]	Loss: 140.511612
Train Epoch: 1 [39680/60000 (66%)]	Loss: 142.047607
Train Epoch: 1 [40960/60000 (68%)]	Loss: 139.073242
Train Epoch: 1 [42240/60000 (70%)]	Loss: 140.667725
Train Epoch: 1 [43520/60000 (72%)]	Loss: 142.093582
Train Epoch: 1 [44800/60000 (75%)]	Loss: 131.476868
Train Epoch: 1 [46080/60000 (77%)]	Loss: 137.830429
Train Epoch: 1 [47360/60000 (79%)]	Loss: 141.102036
Train Epoch: 1 [48640/60000 (81%)]	Loss: 128.376373
Train Epoch: 1 [49920/60000 (83%)]	Loss: 135.808212
Train Epoch: 1 [51200/60000 (85%)]	Loss: 133.896515
Train Epoch: 1 [52480/60000 (87%)]	Loss: 133.259933
Train Epoch: 1 [53760/60000 (90%)]	Loss: 127.026588
Train Epoch: 1 [55040/60000 (92%)]	Loss: 129.372818
Train Epoch: 1 [56320/60000 (94%)]	Loss: 132.166794
Train Epoch: 1 [57600/60000 (96%)]	Loss: 127.940308
Train Epoch: 1 [58880/60000 (98%)]	Loss: 125.580383
====> Epoch: 1 Average loss: 164.6744
====> Test set loss: 128.0015
Train Epoch: 2 [0/60000 (0%)]	Loss: 131.774231
Train Epoch: 2 [1280/60000 (2%)]	Loss: 129.155136
Train Epoch: 2 [2560/60000 (4%)]	Loss: 123.548080
Train Epoch: 2 [3840/60000 (6%)]	Loss: 126.043655
Train Epoch: 2 [5120/60000 (9%)]	Loss: 125.900391
Train Epoch: 2 [6400/60000 (11%)]	Loss: 125.306747
Train Epoch: 2 [7680/60000 (13%)]	Loss: 124.910072
Train Epoch: 2 [8960/60000 (15%)]	Loss: 124.997482
Train Epoch: 2 [10240/60000 (17%)]	Loss: 123.886559
```

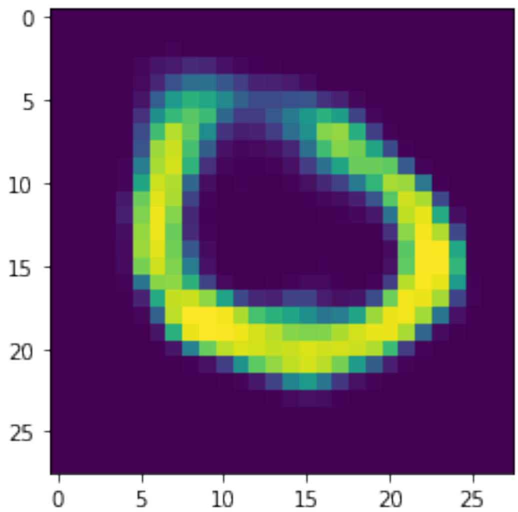
```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
<ipython-input-26-352892a87196> in <module>()
----> 1 to_graph[1][1]

IndexError: index 1 is out of bounds for dimension 0 with size 1
```

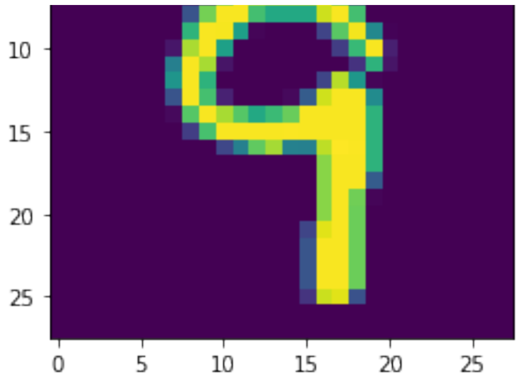
SEARCH STACK OVERFLOW

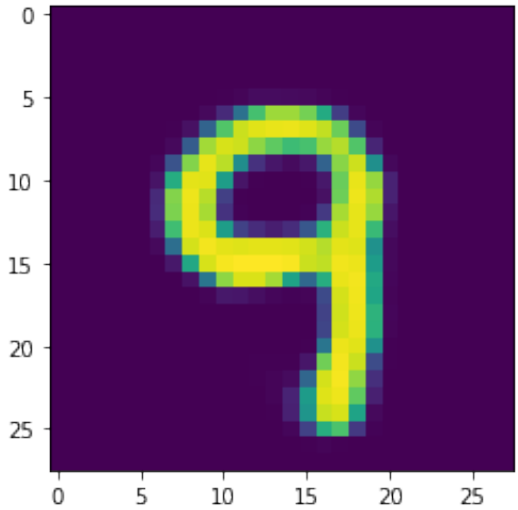
```
to_graph = {}
while True:
 for data, targets in test_loader:
```

```
  for d, t in zip(data, targets):
   if int(t) not in to_graph.keys():
    to_graph[int(t)] = d[0]
   if len(to_graph) == 10:
    break
  if len(to_graph) == 10:
    break
 if len(to_graph) == 10:
    break

for label, data in to_graph.items():
 plt.imshow(data.squeeze())
 plt.show()
 with torch.no_grad():
  data = data.to(device)
  z, _, _ = model(data.view(-1, 784))
  plt.imshow(torch.reshape(z, (28,28)).cpu().numpy())
  plt.show()
```







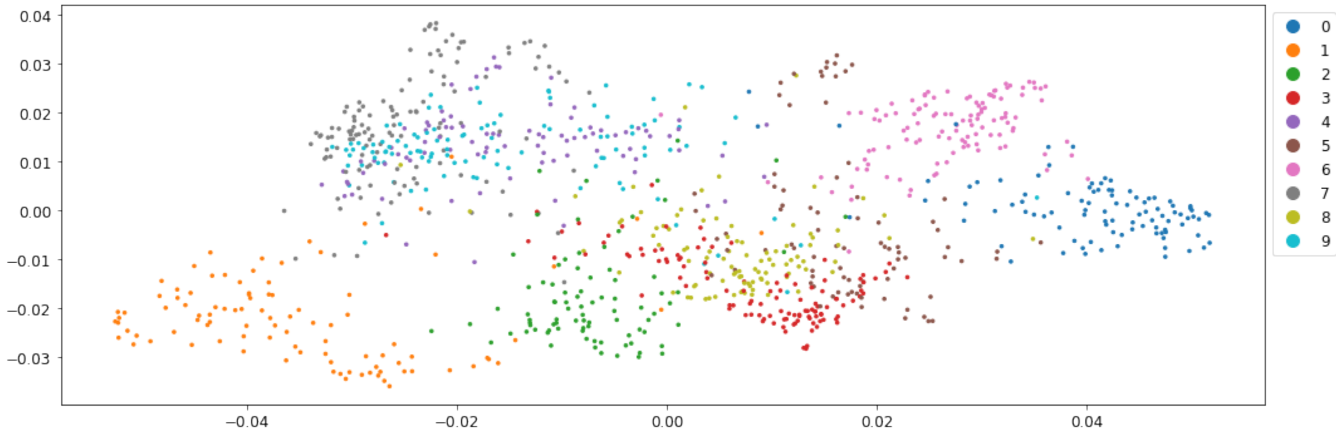




```
1 !pip install phate scprep
```

```
Requirement already satisfied: phate in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: scprep in /usr/local/lib/python3.6/dist-pack
Requirement already satisfied: tasklogger>=1.0 in /usr/local/lib/python3.6/
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/di
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.6/dis
Requirement already satisfied: Deprecated in /usr/local/lib/python3.6/dist-
Requirement already satisfied: s-gd2>=1.5 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: future in /usr/local/lib/python3.6/dist-pack
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/pytho
Requirement already satisfied: graphtools>=1.3.1 in /usr/local/lib/python3.
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.6/
Requirement already satisfied: decorator>=4.3.0 in /usr/local/lib/python3.6
Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.6/dis
Requirement already satisfied: wrapt<2,>=1.10 in /usr/local/lib/python3.6/d
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dis
Requirement already satisfied: pygsp>=0.5.1 in /usr/local/lib/python3.6/dis
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dis
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/pytho
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in 
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dis
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-package
```

```
import phate
import scprep
thousand_loader = torch.utils.data.DataLoader(mnist_train, batch_size = 100(
for data, target in thousand_loader:
  with torch.no_grad():
    data = data.to(device)
    model_input = data.view(-1, 784)# TODO: Turn the 28 by 28 image tensors
    mu, log = model.encode(model_input)
    out = model.reparameterize(mu, log)
    out = out.detach().cpu().numpy()
    labels = target
    break

subsample_data_pc, subsample_meta = scprep.select.subsample(out, labels, n =
data_phate = phate.PHATE().fit_transform(subsample_data_pc)

scprep.plot.scatter2d(data_phate, c=list(subsample_meta), figsize=(15,5), le

# df = {'x': out[:, 0], 'y': out[:, 1], 'label': labels.numpy()}



# data = pd.DataFrame(df)
# facet = sns.lmplot(data=data, x='x', y='y', hue='label',
#                    fit_reg=False, legend=False)

# #add a legend
# leg = facet.ax.legend(bbox_to_anchor=[1, 0.75],
#                          title="label", fancybox=True)

```

```
Calculating PHATE...
  Running PHATE on 1000 observations and 20 variables.
  Calculating graph and diffusion operator...
    Calculating KNN search...
    Calculated KNN search in 0.04 seconds.
    Calculating affinities...
    Calculated affinities in 0.01 seconds.
  Calculated graph and diffusion operator in 0.06 seconds.
  Calculating optimal t...
    Automatically selected t = 30
  Calculated optimal t in 0.71 seconds.
  Calculating diffusion potential...
  Calculated diffusion potential in 0.43 seconds.
  Calculating metric MDS...
  Calculated metric MDS in 1.02 seconds.
Calculated PHATE in 2.23 seconds.
<matplotlib.axes._subplots.AxesSubplot at 0x7f2e58205a90>
```



Question 4.1.1. How does the VAE's latent space compare to the latent space of your previous autoencoder? Do the generated images have more clarity? Is this most noticeable between or within classes?

The latent space seems to be much better defined for the VAE, and the generated images absolutely have more clarity. It is most noticable between classes.

Question 4.1.2. In what situations would a VAE be more useful than a vanilla autoencoder, and when would you prefer a vanilla autoencoder to a VAE?

VAEs should perform better on larger datasets, and they perform better to distinguish between classes. I think vanilla AE should be used first, if they are sufficient, then use it, as it is a simpler model. If the data has a lot of similarities, then an AE should be good, but if it is important to make distinctions between categories, then VAE.

Question 4.1.3. The distance between embeddings in your first autoencoder provided some measure of the similarity between digits. To what extent is this preserved, or improved, by the VAE?

This is preserved less. This is by design of the VAE.

## 4.2 GANs

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torch.optim as optim
import torchvision.datasets as datasets
from torch.autograd import Variable
import imageio
import numpy as np
import matplotlib
import math
from torchvision.utils import make_grid, save_image
from torch.utils.data import DataLoader
from matplotlib import pyplot as plt
from tqdm import tqdm
matplotlib.style.use('ggplot')
```

```
!mkdir outputs
```

```
mkdir: cannot create directory ‘outputs’: File exists
```

```
#### GAN.py
criterion = nn.BCELoss()
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
class Generator(nn.Module):
    def __init__(self, nz):
        super(Generator, self).__init__()
        self.nz = nz # the dimension of the random noise used to seed the Ge
        self.main = nn.Sequential( # nn.sequential is a handy way of combini
            nn.Linear(self.nz, 256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 1024),
            nn.LeakyReLU(0.2),
            nn.Linear(1024, 784),
            nn.Tanh(),
        )
    def forward(self, x):
        return self.main(x).view(-1, 1, 28, 28)

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.n_input = 784
        self.main = nn.Sequential(
            nn.Linear(self.n_input, 1024),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3),
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3),
            nn.Linear(256, 1),
            nn.Sigmoid(),
        )
    def forward(self, x):
        x = x.view(-1, 784)
        return self.main(x)


def train_discriminator(optimizer, real_data, fake_data):
```

```
    """
    Train the discriminator on a minibatch of data.
    INPUTS
        :param optimizer: the optimizer used for training
        :param real_data: the batch of training data
        :param fake_data: the data generated by the generator from random no
    The discriminator will incur two losses: one from trying to classify the
    TODO: Fill in this function.
    It should
    1. Run the discriminator on the real_data and the fake_data
    2. Compute and sum the respective loss terms (described in the assignmen
    3. Backpropogate the loss (e.g. loss.backward()), and perform optimizati
    """
    # optimizer.zero_grad()
    fake_out = discriminator(fake_data)
    real_out = discriminator(real_data)
    y_fake = Variable(torch.zeros(batch_size, 1, device = device))
    y_real = Variable(torch.ones(batch_size, 1, device = device))
    D_real_loss = criterion(real_out, y_real)
    D_fake_loss = criterion(fake_out, y_fake)
    # loss = -0.5 * y_real * torch.clamp(torch.log((real_out)), 1e-3, 1e3) -
    # loss = loss.sum()
    # import pdb; pdb.set_trace()
    loss = (D_fake_loss + D_real_loss) / 2

    loss.backward()
    # optimizer.step()

    # we'll return the loss for book-keeping purposes. (E.g. if you want to

    return loss.item(), optimizer

def train_generator(optimizer, fake_data):
    """
    Performs a single training step on the generator.
    :param optimizer: the optimizer
    :param fake_data: forgeries, created by the generator from random noise.
    :return:  the generator's loss
    TODO: Fill in this function
    It should
    1. Run the discriminator on the fake_data
    2. compute the resultant loss for the generator (as described in the ass
    3. Backpropagate the loss, and perform optimization
    """
    # import pdb; pdb.set_trace()

    # with torch.no_grad():
    # optimizer.zero_grad()
```

```
    fake_out = discriminator(fake_data)
    y = Variable(torch.ones(batch_size, 1).to(device))
    loss = criterion(fake_out, y)
    # loss = -0.5 * y * torch.clamp(torch.log(fake_out), 1e-3, 1e3)
    # loss = loss.sum()
    # import pdb; pdb.set_trace()
    loss.backward()
    # optimizer.step()
    return loss.item(), optimizer

# import data
batch_size = 100
train_data = datasets.MNIST(
    root='../data',
    train=True,
    download=True,
    transform=transforms.ToTensor()
)
train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True)

num_epochs = 1000
nz = 25# dimension of random noise
generator = Generator(nz)
generator = generator.to(device)
discriminator = Discriminator()
discriminator = discriminator.to(device)
g_optimizer = optim.Adam(generator.parameters(), lr=3e-4)
d_optimizer = optim.Adam(discriminator.parameters(), lr=3e-4)
#TODO: Build a training loop for the GAN
# For each epoch, you'll
# 1. Loop through the training data. For each batch, feed random noise into
# 2. Feed the fake data and real data into the train_discriminator and trair
# At the end of each epoch, use the below functions to save a grid of genera
for epoch in range(num_epochs):
    for data, _ in train_loader:
        # perform training
        data = data.to(device)
        g_optimizer.zero_grad()


        noise = torch.randn((batch_size, nz), device=device)
        noise = torch.clamp(noise, 1e-8, 1)
        fake_data = generator(noise)
        gen_loss, g_optimizer = train_generator(optimizer = g_optimizer, fak
        g_optimizer.step()

        d_optimizer.zero_grad()
        noise = torch.randn((batch_size, nz), device=device)
```

```
      noise = torch.clamp(noise, 1e-8, 1)
      fake_data = generator(noise)
      dis_loss, d_optimizer = train_discriminator(optimizer = d_optimizer,


      d_optimizer.step()
    # reshape the image tensors into a grid
    if epoch % 100 == 0:
      print('Epoch: {} \t Gen loss: {} \t Dis loss: {}'.format(epoch, gen_lc
      print('youre past {}'.format(epoch))
    generated_img = make_grid(fake_data)
    # save the generated torch tensor images
    save_image(generated_img, f"outputs/gen_img{epoch}.png")
```

```
Epoch: 0         Gen loss: 9.10543155670166      Dis loss: 0.48131835460662
youre past 0
Epoch: 100       Gen loss: 1.3410712480545044    Dis loss: 0.46736103296279
youre past 100
```

Question 4.2.1. Which generates more realistic images: your GAN, or your VAE? Why do you think this is?

From what I saw, the VAE generated more realistic images. I assume this is because there is an actual input to the VAE to reconstruct it whereas the GAN generalizes over the noise

Question 4.2.2. Does your GAN appear to generate all digits in equal number, or has it specialized in a smaller number of digits? If so, why might this be?

It seems to generate 0s more than anything. This is probably because so many numbers have curves, 2, 3, 5, 6, 8, 9, 0 that having a number that is essentially the average would be the easiest for the generator to learn. It also seems to make a lot of 3s, possibly because the left side of many numbers is open. interestingly enough, the generator doesn't appear to make many 8s.

```
model = LogisticRegression().to(device)
# initialize the optimizer, and set the learning rate
SGD = torch.optim.SGD(model.parameters(), lr = 5e-2) # This is absurdly high
# initialize the loss function. You don't want to use this one, so change it
loss_fn = torch.nn.CrossEntropyLoss()
batch_size = 128
train_loader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_siz
test_loader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size,
train_loss, train_acc, test_loss, test_acc = train(model = model,loss_fn = l
```

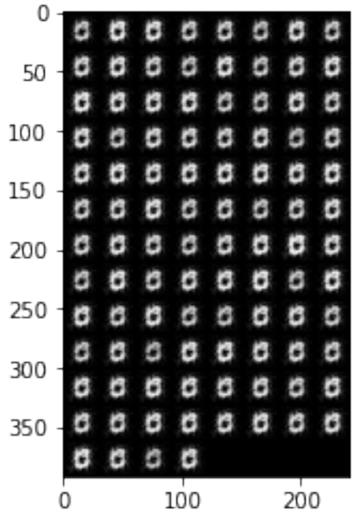
```
!unzip to_classify.zip
```

```
Archive:  to_classify.zip
   creating: to_classify/
  inflating: to_classify/gen_img906.png
  inflating: to_classify/gen_img908.png
  inflating: to_classify/gen_img913.png
  inflating: to_classify/gen_img914.png
  inflating: to_classify/gen_img923.png
  inflating: to_classify/gen_img925.png
  inflating: to_classify/gen_img928.png
  inflating: to_classify/gen_img936.png
  inflating: to_classify/gen_img940.png
  inflating: to_classify/gen_img943.png
  inflating: to_classify/gen_img946.png
  inflating: to_classify/gen_img947.png
  inflating: to_classify/gen_img951.png
  inflating: to_classify/gen_img954.png
  inflating: to_classify/gen_img955.png
  inflating: to_classify/gen_img956.png
  inflating: to_classify/gen_img957.png
  inflating: to_classify/gen_img963.png
  inflating: to_classify/gen_img968.png
  inflating: to_classify/gen_img971.png
  inflating: to_classify/gen_img972.png
  inflating: to_classify/gen_img973.png
  inflating: to_classify/gen_img978.png
  inflating: to_classify/gen_img981.png
  inflating: to_classify/gen_img999.png
```

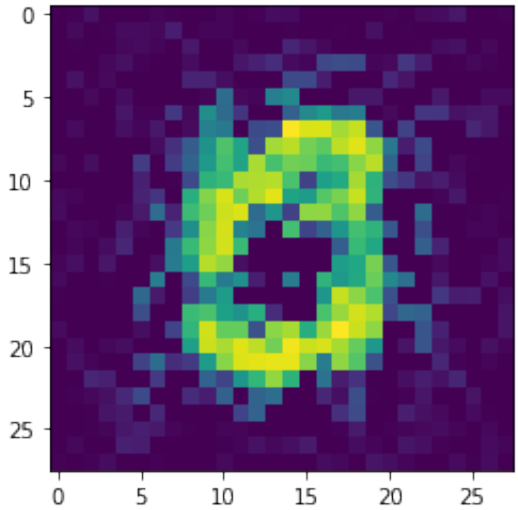
```
import matplotlib.pyplot as plt

from PIL import Image
import torchvision.transforms.functional as TF
import os
from torchvision.transforms import Grayscale
scaler = Grayscale(1)
for filename in os.listdir('to_classify'):
  print('Generated')
  image = Image.open(os.path.join('to_classify',filename))
  plt.imshow(image)
  plt.show()
  crop_rectangle = (2, 2, 30, 30) #crop to 28 x 28
  cropped_im = image.crop(crop_rectangle)
  cropped_im = scaler(cropped_im) #convert to grayscale
  print('Cropped/greyscaled')
  plt.imshow(cropped_im)
  plt.show()
  x = TF.to_tensor(cropped_im).to(device)
  model_input = x.view(-1, 784)
```

```
out = model(model_input)
arg_maxed = torch.argmax(out, dim = 1)
print('predicted: {}'.format(arg_maxed.item()))

```

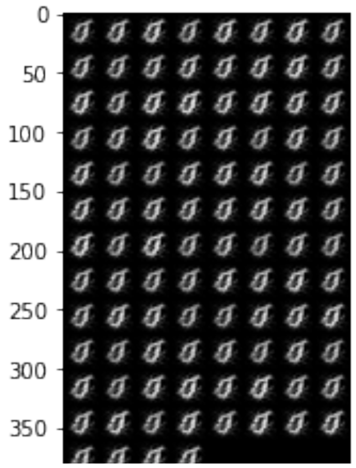
```
Generated
```

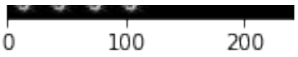


```
Cropped/greyscaled
```

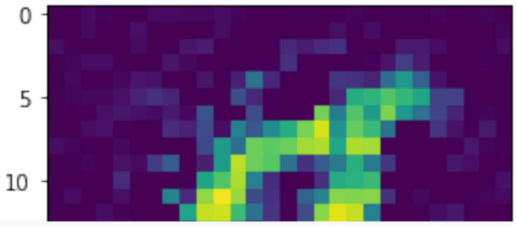


```
predicted: 0
Generated
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:1639: UserWa
  warnings.warn("nn.functional.sigmoid is deprecated. Use torch.sigmoid i
```






Cropped/greyscaled




# 5 Information Theory

```
!pip install pyemd
```

```
Requirement already satisfied: pyemd in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: numpy<2.0.0,>=1.9.0 in /usr/local/lib/python
```

```
from time import perf_counter
import torch
from pyemd import emd
from scipy.stats import entropy
import numpy as np
import pickle
import sklearn.neighbors
from scipy.spatial import distance_matrix
import torchvision.datasets as datasets
import torchvision.transforms as transforms

mnist_train = datasets.MNIST(root = 'data', train=True, download=True, trans
mnist_test = datasets.MNIST(root = 'data', train=False, download=True,transf
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to
76%   7553024/9912422 [00:00<00:13, 171660.09it/s]
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to
      32768/? [00:00<00:00, 350126.37it/s]
Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to d

1%    16384/1648877 [00:00<00:12, 126950.32it/s]
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to d
      0/? [00:00<?, ?it/s]
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
Processing...
Done!
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:480: U
  return torch.from_numpy(parsed.astype(m[2], copy=False)).view(*s)
```

```
def mmd(X,Y, kernel_fn):
    """
    Implementation of Maximum Mean Discrepancy.
    :param X: An n x 1 numpy vector containing the samples from distributior
    :param Y: An n x 1 numpy vector containing the samples from distributior
    :param kernel_fn: supply the kernel function to use.
    :return: the maximum mean discrepancy:
    MMD(X,Y) = Expected value of k(X,X) + Expected value of k(Y,Y) - Expecte
    where k is a kernel function
    """
    mmd = torch.mean(kernel_fn(X, X)) + torch.mean(kernel_fn(Y, Y)) - torch.
    return mmd


def kernel(A, B):
    """
    A gaussian kernel on two arrays.
    :param A: An n x d numpy matrix containing the samples from distributior
    :param B: An n x d numpy matrix containing the samples from distributior
    :return K:  An n x n numpy matrix k, in which k_{i,j} = e^{-||A_i - B_j|
    """
    sigma = 1
    K = torch.exp(-(torch.abs(A-B)**2 / (2.0 * sigma**2)))
    return K
```

```
def compute_kl(a, b):
  t_start = perf_counter()
  kl = entropy(a, b)
  t_stop = perf_counter()
  return np.mean(kl), t_stop - t_start
def compute_emd(a, b):
  kde_a = sklearn.neighbors.KernelDensity(kernel="gaussian", bandwidth=0.5).
  a_samples = kde_a.score_samples(a)
  kde_b = sklearn.neighbors.KernelDensity(kernel="gaussian", bandwidth=0.5).
  b_samples = kde_b.score_samples(b)
  dist = distance_matrix(np.expand_dims(a_samples, 1), np.expand_dims(b_samp
  t_start = perf_counter()
  emd_out = emd(np.exp(a_samples), np.exp(b_samples), dist)
  t_stop = perf_counter()
  return emd_out, t_stop - t_start
def compute_mmd(a, b):
  t_start = perf_counter()
  mmd_out = mmd(a, b, kernel)
  t_stop = perf_counter()
  return mmd_out, t_stop - t_start
def get_all(a, b):
  kl1, kl1_time = compute_kl(a, b)
  kl2, kl2_time = compute_kl(b, a)

  emd_out, emd_time = compute_emd(a, b)

  mmd_out, mmd_time = compute_mmd(a, b)

  print('KL a, b: {} \t time: {}'.format(kl1, kl1_time))
  print('KL b, a: {} \t time: {}'.format(kl2, kl2_time))
  print('EMD: {} \t time: {}'.format(emd_out, emd_time))
  print('MMD: {} \t time: {}'.format(mmd_out, mmd_time))
```

```
# PART 1
a = torch.rand((1000, 3))
b = torch.empty(1000, 3).normal_(mean=0,std=1)

#entropy(a, b), entropy(b,a) both will return [inf, inf, inf]

b[b==0] = 1e-8
#entropy(a, b), entropy(b,a) both still both return [inf, inf, inf]
b = torch.abs(b)
get_all(a, b)
```

```
KL a, b: 0.6029940843582153      time: 0.004756203999988884
KL b, a: 0.5953423976898193      time: 0.0003583929999990687
EMD: 947.8049488395836   time: 0.0982579429999646
MMD: 0.3636596202850342          time: 0.00039149700000962184
```

Question 5.1.1. Based on the above measures alone, which divergence seems most accurate?

I think either KL or MMD. EMD seems to be very high. However, since I know the values are uniform vs random, I imagine on average the distance between each point is < 0.5, so I think MMD is the most accurate.

```
# PART 2
indices = torch.randperm(len(mnist_test))[:2000]

subset1 = torch.utils.data.Subset(mnist_test, indices[:1000])
subset2 = torch.utils.data.Subset(mnist_test, indices[1000:])

sub1 = []
for x, y in subset1:
  sub1.append(x)

a = torch.cat(sub1, dim = 0).view(-1, 784)

sub2 = []
for x, y in subset2:
  sub2.append(x)

b = torch.cat(sub2, dim = 0).view(-1, 784)

a[a==0] = 1e-8
b[b==0] = 1e-8

get_all(a, b)
```

```
KL a, b: 10.58070182800293       time: 0.028992849000019305
KL b, a: 10.555280685424805      time: 0.028606792000005044
EMD: 3.4907284985548466e-83      time: 0.09398919599999545
MMD: 0.11188805103302002         time: 0.010181770999963646
```

```
#PART 3
with open('p5_output.p', 'rb') as f:
  b = pickle.load(f)
b = b.view(-1, 784)
# a[a==0] = 1e-8
b[b==0] = 1e-8
b = torch.abs(b)
get_all(a, b)
```

```
KL a, b: 2.190413236618042       time: 0.03119231400000899
KL b, a: 8.476593971252441       time: 0.03095107100000405
EMD: 2.5011979219961465e-75      time: 0.10797177799997826
MMD: 0.30129003524780273         time: 0.011146196999959557
```

Question 5.3.1. Which divergence or distance showed the greatest discrepancy between the comparison between real MNIST data and the comparison with the GAN?

In KL divergence when the GAN generated tensor is the first argument created the greatest discrepancy.

Question 5.3.2. Which of these information measures would you recommend for judging a GAN's output? Why?

I think using MMD would be the best. The discrepancy between the order of the KL divergence is too great. EMD seems to measure the distance to be incredibly small, which I know that cannot be the case. This leaves MMD which shows there is some discrepancy, but not too incredibly much, which seems about accurate for a GAN.

Question 5.3.3. How do the runtimes of these measures compare?

Based on the previous experiments, KL calculation seems to take much longer. EMD seems to be consistently the slowest and mmd was faster than KL in this case, but it doesn't seem to be the same for every experiment.

```
1
```