Basic Instructions

1. Enter your Name, UID and Link to Google Drive in the provided space.
2. Submit the assignment to Gradescope.
3. Do not change anything unless told to do so by the instructions. We give you a framework, and until Exercise 10, you should adhere to that framework as closely as possible.

Final Submission Deadline: May 11, 5:00pm

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Link to Google Drive :
https://colab.research.google.com/drive/1xUYxsdmV3iVZRpMP-ARfCekU5zA5Aiqa?usp=sharing

Preliminaries (IMPORTANT, MUST READ)

This assignment is meant to enrich your understanding of VAEs based on what was covered in lecture.

This assignment is all bonus, but some of it should be considered "core" components, and we will give no credit unless they are all in working order. These components are represented by Exercises 1-5. For example, if you complete Exercises 1-4 only, you will receive no credit for this assignment. Together, they are worth **50%** of the points for this assignment.

Exercises 6-10, on the other hand, are **extra** components. You may complete any number of these to increase the number of bonus points you receive for the assignment. Together, they allow you to earn the other **50%** of the points, but note that they can be completed cafeteria style -- pick whatever seems edible and eat it. No need to buy/eat everything, unless you really want to. Doing extra exercises will not increase your grade for the assignment: **hard cap at 100%**.

Consider 5 students, A, B, C, D, and E.

Student A completes Exercises 1-4. They get a 0.

Student B completes 1-5. They get a 50.

Student C completes 1-6. They get a 60.

Student D completes 1-5, 7, 9, and 10. They get a 100.

Student E completes 1-10. They also get a 100.

Imports and Parameter Settings

```
%matplotlib inline
import os

import torch
import torch.nn as nn
import torch.nn.functional as F

# 2-d latent space, parameter count in same order of magnitude
# as in the original VAE paper (VAE paper has about 3x as many)
latent_dims = 2
num_epochs = 100
batch_size = 128
capacity = 64
learning_rate = 1e-3
variational_beta = 1
use_gpu = True
```

MNIST Data Loading

MNIST images show digits from 0-9 in 28x28 grayscale images. We do not center them at 0, because we will be using a binary cross-entropy loss that treats pixel values as probabilities in [0,1]. We create both a training set and a test set.

```
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
from torchvision.datasets import MNIST

img_transform = transforms.Compose([
    transforms.ToTensor()
])

train_dataset = MNIST(root='./data/MNIST', download=True, train=True,
transform=img_transform)
train_dataloader = DataLoader(train_dataset, batch_size=batch_size,
shuffle=True)

test_dataset = MNIST(root='./data/MNIST', download=True, train=False,
transform=img_transform)
test_dataloader = DataLoader(test_dataset, batch_size=batch_size,
shuffle=True)
```

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

100%|██████████| 9912422/9912422 [00:00<00:00, 326322032.89it/s]
```

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

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

100%|██████████| 28881/28881 [00:00<00:00, 31710914.61it/s]

Extracting ./data/MNIST/MNIST/raw/train-labels-idx1-ubyte.gz to
./data/MNIST/MNIST/raw

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

100%|██████████| 1648877/1648877 [00:00<00:00, 188034023.83it/s]

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

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

100%|██████████| 4542/4542 [00:00<00:00, 2616471.47it/s]

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

Exercise 1: Define Encoder

We use a convolutional encoder and decoder, which generally gives better performance than fully connected versions that have the same number of parameters.

In convolution layers, we increase the channels as we approach the bottleneck, but note that the total number of features still decreases, since the channels increase by a factor of 2 in each convolution, but the spatial size decreases by a factor of 4.

Kernel size 4 is used to avoid biasing problems described here: https://distill.pub/2016/deconv-checkerboard/

TODO: complete Encoder forward (3-5 lines of code)

```
class Encoder(nn.Module):
    def __init__(self):
```

```
        super(Encoder, self).__init__()
        cap = capacity
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=cap,
kernel_size=4, stride=2, padding=1) # out: capacity x 14 x 14
        self.conv2 = nn.Conv2d(in_channels=cap, out_channels=cap*2,
kernel_size=4, stride=2, padding=1) # out: capacity x 7 x 7
        self.fc_mu = nn.Linear(in_features=cap*2*7*7,
out_features=latent_dims)
        self.fc_logvar = nn.Linear(in_features=cap*2*7*7,
out_features=latent_dims)

    def forward(self, x):
        ### TODO: implement forward
        ## hint: use relu as activation for each conv layer
        ## hint: flatten after self.conv2
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = x.view(x.size(0), -1)
        x_mu = self.fc_mu(x)
        x_logvar = self.fc_logvar(x)
        return x_mu, x_logvar
```

Exercise 2: Define Decoder

TODO: complete Decoder init (3-4 lines of code)

```
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder, self).__init__()
        cap = capacity
        ### TODO: define Decoder
        ## hint: define an FC layer with the appropriate number of
in_channels for the output of the encoder
        ## hint: fc out_channels need to provide what self.conv2
expects
        #self.fc = ...
        self.fc = nn.Linear(in_features=latent_dims,
out_features=cap*2*7*7)
        ## hint: two up-conv layers that are essentially the converse
of the original convolutional layers
        #self.conv2 = nn.ConvTranspose2d(...)
        #self.conv1 = ...
        self.conv2 = nn.ConvTranspose2d(in_channels=cap*2,
out_channels=cap, kernel_size=4, stride=2, padding=1)
        self.conv1 = nn.ConvTranspose2d(in_channels=cap,
out_channels=1, kernel_size=4, stride=2, padding=1)

    def forward(self, x):
        x = self.fc(x)
```

```
        x = x.view(x.size(0), capacity*2, 7, 7) # unflatten batch of
feature vectors to a batch of multi-channel feature maps
        x = F.relu(self.conv2(x))
        x = torch.sigmoid(self.conv1(x)) # last layer before output is
sigmoid, since we are using BCE as reconstruction loss
        return x
```

Exercise 3: Define Variational Autoencoder

TODO: complete VAE init (2 lines of code)

TODO: complete VAE forward (2 lines of code)

TODO: complete VAE latent_sample (2 lines of code)

```
class VariationalAutoencoder(nn.Module):
    def __init__(self):
        super(VariationalAutoencoder, self).__init__()
        ### TODO: implement constructor, set encoder and decoder
        self.encoder = Encoder()
        self.decoder = Decoder()

    def forward(self, x):
        ### TODO: finish implementation of forward
        ## hint: call encoder
        latent_mu, latent_logvar = self.encoder(x)
        latent = self.latent_sample(latent_mu, latent_logvar)
        ## hint: call decoder
        x_recon = self.decoder(latent)
        return x_recon, latent_mu, latent_logvar

    def latent_sample(self, mu, logvar):
        if self.training:
            ### TODO: implement the missing parts of the
reparameterization trick
            ## hint: calculate std
            std = torch.exp(0.5 * logvar)
            ## hint: calculate eps
            eps = torch.randn_like(std)
            return eps.mul(std).add_(mu)
        else:
            return mu
```

Exercise 4: Define VAE Loss

VAE loss is a linear combination of the reconstruction loss (computed as BCE between original and reconstructed image) and the KL-Divergence between the prior distriubtrion over latent vectors and the distribution estimated by the gerenated for the given image. Here, we give you the KL term and the combintation, but have you implement the reconstruction loss.

TODO: Reconstruction loss (1 line of code)

```
def vae_loss(recon_x, x, mu, logvar):
    # recon_x is the probability of a multivariate Bernoulli distribution p.
    # -log(p(x)) is then the pixel-wise binary cross-entropy.
    # Averaging or not averaging the binary cross-entropy over all pixels here
    # is a subtle detail with big effect on training, since it changes the weight
    # we need to pick for the other loss term by several orders of magnitude.
    # Not averaging is the direct implementation of the negative log likelihood,
    # but averaging makes the weight of the other loss term independent of the image resolution.

    ### TODO: define recon_loss
    ## hint: use binary cross entropy
    ## hint: use reduction='sum' argument
    ## hint: flatten both images to shape (1, 784)
    recon_loss = F.binary_cross_entropy(recon_x.view(-1, 784), x.view(-1, 784), reduction='sum')


    # KL-divergence between the prior distribution over latent vectors
    # (the one we are going to sample from when generating new images)
    # and the distribution estimated by the generator for the given image.
    kldivergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())

    return recon_loss + variational_beta * kldivergence
```

Exercise 5: Train VAE

TODO: complete training loop (3 lines of code)

```
vae = VariationalAutoencoder()

device = torch.device("cuda:0" if use_gpu and torch.cuda.is_available() else "cpu")
vae = vae.to(device)

num_params = sum(p.numel() for p in vae.parameters() if p.requires_grad)
print('Number of parameters: %d' % num_params)
assert num_params == 308357

optimizer = torch.optim.Adam(params=vae.parameters(),
```

```python
lr=learning_rate, weight_decay=1e-5)

# set to training mode
vae.train()

train_loss_avg = []

print('Training ...')
for epoch in range(num_epochs):
    train_loss_avg.append(0)
    num_batches = 0

    for image_batch, _ in train_dataloader:

        ## hint: send images to gpu (if using)
        image_batch = image_batch.to(device)

        ## hint: pass images through vae
        recon_images, mu, logvar = vae(image_batch)

        ## hint: compute reconstruction error (calculate loss)
        loss = vae_loss(recon_images, image_batch, mu, logvar)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        train_loss_avg[-1] += loss.item()
        num_batches += 1

    train_loss_avg[-1] /= num_batches
    print('Epoch [%d / %d] average reconstruction error: %f' %
(epoch+1, num_epochs, train_loss_avg[-1]))
```

```
Number of parameters: 308357
Training ...
Epoch [1 / 100] average reconstruction error: 23331.035885
Epoch [2 / 100] average reconstruction error: 21012.361062
Epoch [3 / 100] average reconstruction error: 20458.582887
Epoch [4 / 100] average reconstruction error: 20162.439441
Epoch [5 / 100] average reconstruction error: 19970.611426
Epoch [6 / 100] average reconstruction error: 19836.093523
Epoch [7 / 100] average reconstruction error: 19717.021824
Epoch [8 / 100] average reconstruction error: 19630.977776
Epoch [9 / 100] average reconstruction error: 19556.576062
Epoch [10 / 100] average reconstruction error: 19478.480354
Epoch [11 / 100] average reconstruction error: 19426.369411
Epoch [12 / 100] average reconstruction error: 19369.225557
Epoch [13 / 100] average reconstruction error: 19333.266699
Epoch [14 / 100] average reconstruction error: 19281.776807
```

```
Epoch [15 / 100] average reconstruction error: 19235.815517
Epoch [16 / 100] average reconstruction error: 19196.971349
Epoch [17 / 100] average reconstruction error: 19163.675175
Epoch [18 / 100] average reconstruction error: 19131.667890
Epoch [19 / 100] average reconstruction error: 19099.667496
Epoch [20 / 100] average reconstruction error: 19069.408363
Epoch [21 / 100] average reconstruction error: 19041.030779
Epoch [22 / 100] average reconstruction error: 19010.992577
Epoch [23 / 100] average reconstruction error: 18995.304269
Epoch [24 / 100] average reconstruction error: 18961.280794
Epoch [25 / 100] average reconstruction error: 18935.645720
Epoch [26 / 100] average reconstruction error: 18919.690530
Epoch [27 / 100] average reconstruction error: 18897.946016
Epoch [28 / 100] average reconstruction error: 18879.784486
Epoch [29 / 100] average reconstruction error: 18855.784355
Epoch [30 / 100] average reconstruction error: 18839.158715
Epoch [31 / 100] average reconstruction error: 18820.056416
Epoch [32 / 100] average reconstruction error: 18804.434108
Epoch [33 / 100] average reconstruction error: 18792.742325
Epoch [34 / 100] average reconstruction error: 18764.832044
Epoch [35 / 100] average reconstruction error: 18755.947828
Epoch [36 / 100] average reconstruction error: 18745.408418
Epoch [37 / 100] average reconstruction error: 18726.653427
Epoch [38 / 100] average reconstruction error: 18703.629302
Epoch [39 / 100] average reconstruction error: 18707.174894
Epoch [40 / 100] average reconstruction error: 18685.315680
Epoch [41 / 100] average reconstruction error: 18676.474628
Epoch [42 / 100] average reconstruction error: 18658.743830
Epoch [43 / 100] average reconstruction error: 18646.947087
Epoch [44 / 100] average reconstruction error: 18636.770764
Epoch [45 / 100] average reconstruction error: 18630.588424
Epoch [46 / 100] average reconstruction error: 18609.914294
Epoch [47 / 100] average reconstruction error: 18612.559112
Epoch [48 / 100] average reconstruction error: 18602.140292
Epoch [49 / 100] average reconstruction error: 18591.362036
Epoch [50 / 100] average reconstruction error: 18581.109429
Epoch [51 / 100] average reconstruction error: 18566.431724
Epoch [52 / 100] average reconstruction error: 18551.937954
Epoch [53 / 100] average reconstruction error: 18541.219656
Epoch [54 / 100] average reconstruction error: 18539.078618
Epoch [55 / 100] average reconstruction error: 18526.154588
Epoch [56 / 100] average reconstruction error: 18516.453392
Epoch [57 / 100] average reconstruction error: 18513.169822
Epoch [58 / 100] average reconstruction error: 18493.469450
Epoch [59 / 100] average reconstruction error: 18501.057030
Epoch [60 / 100] average reconstruction error: 18501.684504
Epoch [61 / 100] average reconstruction error: 18488.239722
Epoch [62 / 100] average reconstruction error: 18481.951570
Epoch [63 / 100] average reconstruction error: 18467.241205
Epoch [64 / 100] average reconstruction error: 18461.752796
```

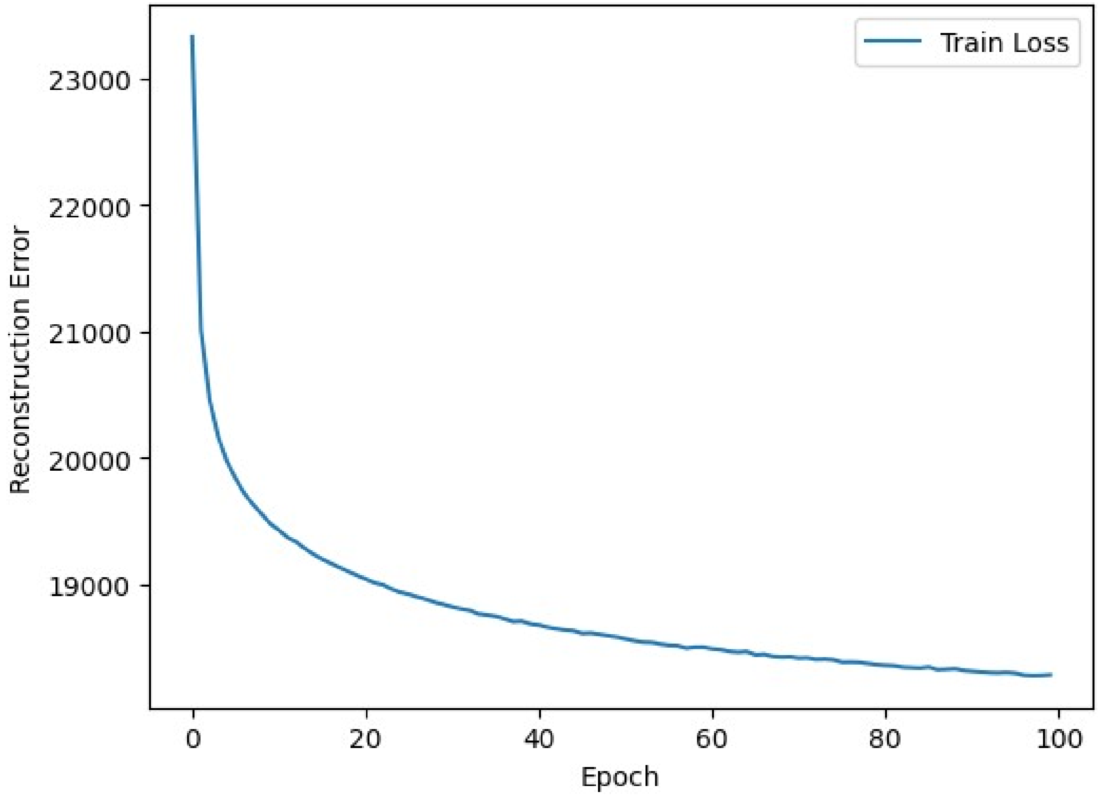
```
Epoch [65 / 100] average reconstruction error: 18466.363852
Epoch [66 / 100] average reconstruction error: 18439.941419
Epoch [67 / 100] average reconstruction error: 18444.364712
Epoch [68 / 100] average reconstruction error: 18427.641491
Epoch [69 / 100] average reconstruction error: 18422.757908
Epoch [70 / 100] average reconstruction error: 18424.582629
Epoch [71 / 100] average reconstruction error: 18415.071241
Epoch [72 / 100] average reconstruction error: 18416.856341
Epoch [73 / 100] average reconstruction error: 18404.713882
Epoch [74 / 100] average reconstruction error: 18407.524010
Epoch [75 / 100] average reconstruction error: 18401.131632
Epoch [76 / 100] average reconstruction error: 18382.330634
Epoch [77 / 100] average reconstruction error: 18383.385049
Epoch [78 / 100] average reconstruction error: 18381.489970
Epoch [79 / 100] average reconstruction error: 18372.266860
Epoch [80 / 100] average reconstruction error: 18362.849409
Epoch [81 / 100] average reconstruction error: 18357.844346
Epoch [82 / 100] average reconstruction error: 18354.690765
Epoch [83 / 100] average reconstruction error: 18342.753506
Epoch [84 / 100] average reconstruction error: 18339.227041
Epoch [85 / 100] average reconstruction error: 18336.166667
Epoch [86 / 100] average reconstruction error: 18344.531013
Epoch [87 / 100] average reconstruction error: 18322.744717
Epoch [88 / 100] average reconstruction error: 18325.853382
Epoch [89 / 100] average reconstruction error: 18330.732938
Epoch [90 / 100] average reconstruction error: 18316.769146
Epoch [91 / 100] average reconstruction error: 18310.485102
Epoch [92 / 100] average reconstruction error: 18304.685788
Epoch [93 / 100] average reconstruction error: 18300.220951
Epoch [94 / 100] average reconstruction error: 18298.103330
Epoch [95 / 100] average reconstruction error: 18301.373722
Epoch [96 / 100] average reconstruction error: 18295.228988
Epoch [97 / 100] average reconstruction error: 18278.850721
Epoch [98 / 100] average reconstruction error: 18275.346317
Epoch [99 / 100] average reconstruction error: 18276.734816
Epoch [100 / 100] average reconstruction error: 18281.550871
```

Exercise 6: Plot Training Curve (10 points)

TODO: create plot (at least 3 lines of code)

```python
import matplotlib.pyplot as plt
plt.ion()

fig = plt.figure()
### TODO: fplot training loss over epochs, include labels!
plt.plot(train_loss_avg, label='Train Loss')
plt.xlabel('Epoch')
plt.ylabel('Reconstruction Error')
```

```
plt.legend()
plt.show()
```



Exercise 7: Evaluate on the Test Set (10 points)

Report average reconstruction error on the entire test test.

TODO: complete VAE init (~12 lines of code)

```
# set to evaluation mode
vae.eval()

test_loss_avg, num_batches = 0, 0

### TODO: compute test_loss_avg by iterating over test set
for image_batch, _ in test_dataloader:

    image_batch = image_batch.to(device)

    # pass images through vae
    recon_images, mu, logvar = vae(image_batch)

    # compute reconstruction error
    loss = vae_loss(recon_images, image_batch, mu, logvar)
```

```
        test_loss_avg += loss.item()
        num_batches += 1

test_loss_avg /= num_batches
print('average reconstruction error: %f' % (test_loss_avg))
```

```
average reconstruction error: 19060.820000
```

Exercise 8: Visualize Reconstructions (20 points)

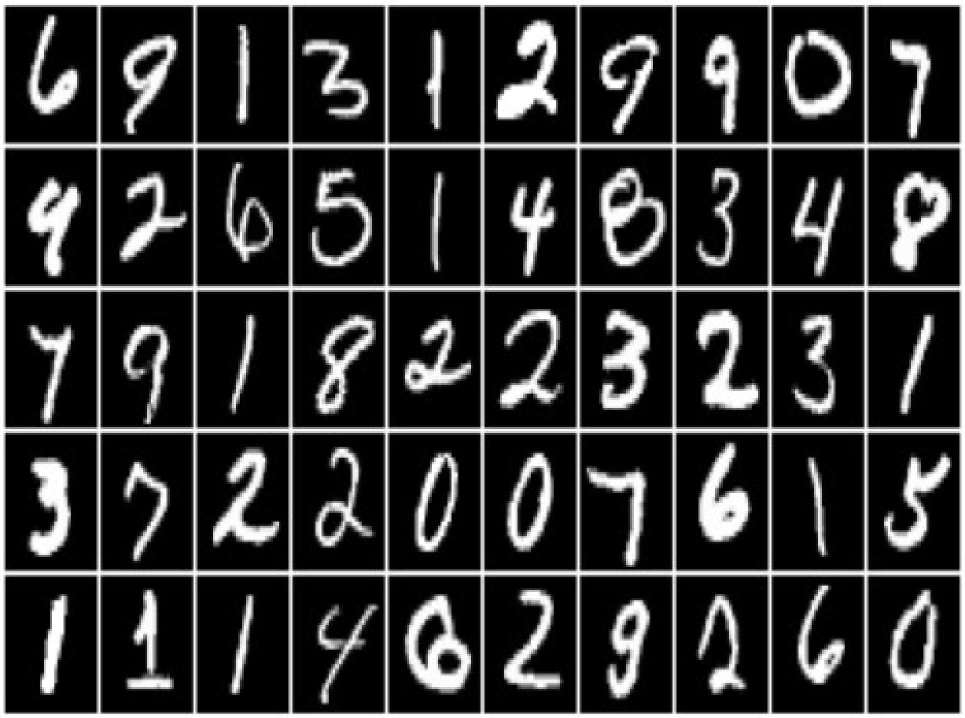
Create a figure that shows, in a digestible format, at least 50 test images, and the reconstructions corresponding to those images. The figure should consist of two grids, the first containing the test images, the second containing the reconstructions.

TODO: show images and reconstructions (>20 lines of code)

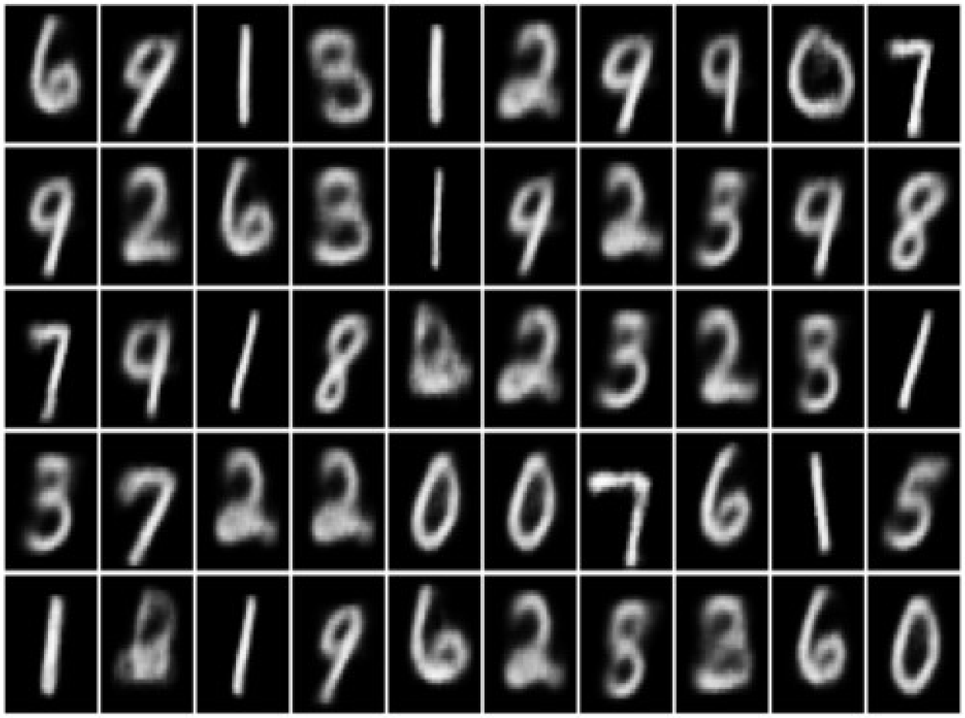
```
import numpy as np
import matplotlib.pyplot as plt
plt.ion()

import torchvision.utils

vae.eval()

# hint: don't forget to "clamp" if necessary
# hint: iter(test_dataloader).next() retrieves a batch
# hint: torchvision.utils.make_grid is your friend, but not necessary

# First, visualize the original images
print('Original images')
image_batch, _ = next(iter(test_dataloader))
grid_img = torchvision.utils.make_grid(image_batch[:50], nrow=10,
padding=1, pad_value=1)
np_grid_img = grid_img.numpy().transpose((1, 2, 0))
plt.imshow(np_grid_img, cmap='gray', aspect='auto')
plt.axis('off')
plt.show()

# Reconstruct and visualize the images using the vae
print('VAE reconstruction:')
image_batch = image_batch.to(device)
reconstructed_images, _, _ = vae(image_batch)
reconstructed_images = reconstructed_images.clamp(0, 1)
reconstructed_grid =
torchvision.utils.make_grid(reconstructed_images.cpu()[:50], nrow=10,
padding=1, pad_value=1)
np_reconstructed_grid = reconstructed_grid.numpy().transpose((1, 2,
0))
plt.imshow(np_reconstructed_grid, cmap='gray', aspect='auto')
```

```
plt.axis('off')
plt.show()
```

```
Original images
```



```
VAE reconstruction:
```



Exercise 9: VAE as a Generator (20 points)

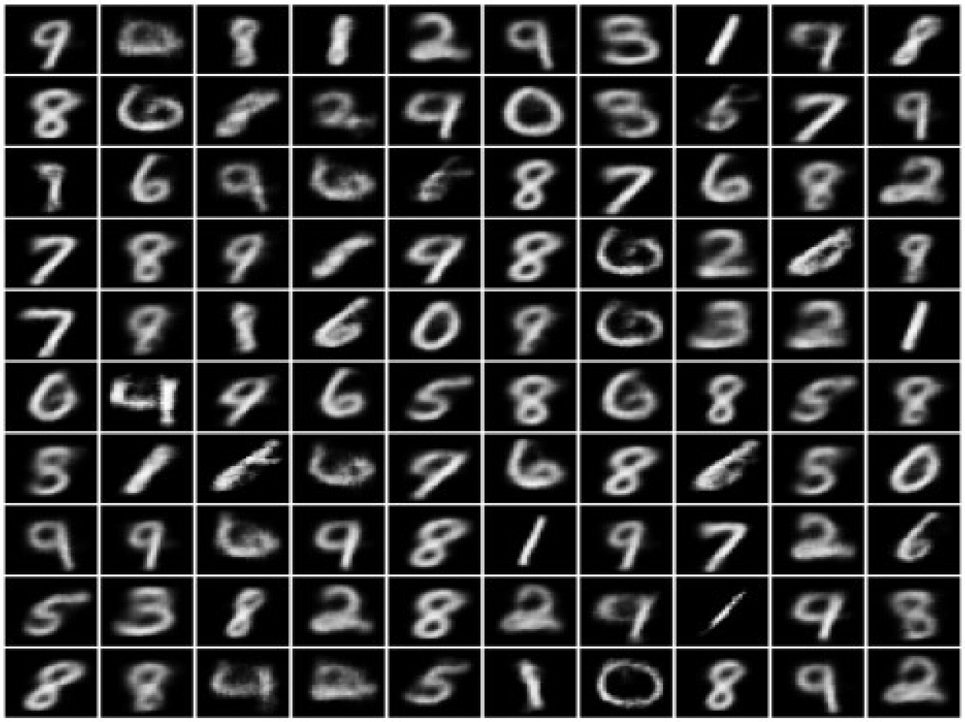
A VAE can generate new digits by drawing latent vectors from the prior distribution. Although the generated digits are not perfect, they are usually better than for a non-variational Autoencoder (compare results for the 10d VAE to the results for the autoencoder).

Similar to autoencoders, the manifold of latent vectors that decode to valid digits is sparser in higher-dimensional latent spaces. Increasing the weight of the KL-divergence term in the loss (increasing `variational_beta`) makes the manifold less sparse at the cost of a lower-quality reconstruction.

TODO: show 100 generated images (~10 lines of code)

```
vae.eval()

with torch.no_grad():
    # TODO: plot 100 "generated" digits in a grid
    # hint: these must be generated from random latent vector, not
reconstructed based on some image
    latent_dim = vae.encoder.fc_mu.out_features
    random_latent_vectors = torch.randn(100, latent_dim).to(device)
    generated_images = vae.decoder(random_latent_vectors)
    generated_images = generated_images.clamp(0, 1)
    generated_grid =
torchvision.utils.make_grid(generated_images.cpu(), nrow=10,
padding=1, pad_value=1)
```

```python
np_generated_grid = generated_grid.numpy().transpose((1, 2, 0))
plt.imshow(np_generated_grid, cmap='gray', aspect='auto')
plt.axis('off')
plt.show()
```



Exercise 10: Think you can do better? (20 points)

Feel free to change any piece of your pipeline to try to improve performance. However, don't make the changes above, make them below. For example, if you want to define a different VAE, define it somewhere below this text block. If you define new parameters, same thing; do so below this block.

Provide evidence that the changes you made resulted in some kind of improvement. Be robust in how you "prove" this. This is a bonus assignment, so don't expect the graders to make any leaps or inferences on your behalf.

TODO: improve reconstruction loss, image quality, or something else, up to you!

Improvements Made

I have increased the weight of the KL-divergence term (*variational_beta*) which should encourage the model to ensure the learned latent distribution aligns more closely with a unit Gaussian, potentially improving the quality of generated samples. The quality is improved and the each image digits are not as blurry as before.

```python
class ImprovedEncoder(nn.Module):
    def __init__(self, capacity=64):
        super(ImprovedEncoder, self).__init__()
```

```
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=capacity,
kernel_size=4, stride=2, padding=1)
        self.conv2 = nn.Conv2d(in_channels=capacity,
out_channels=capacity*2, kernel_size=4, stride=2, padding=1)
        self.fc_mu = nn.Linear(in_features=capacity*2*7*7,
out_features=latent_dims)
        self.fc_logvar = nn.Linear(in_features=capacity*2*7*7,
out_features=latent_dims)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = x.view(x.size(0), -1)
        x_mu = self.fc_mu(x)
        x_logvar = self.fc_logvar(x)
        return x_mu, x_logvar


class ImprovedDecoder(nn.Module):
    def __init__(self, capacity=64):
        super(ImprovedDecoder, self).__init__()
        self.fc = nn.Linear(in_features=latent_dims,
out_features=capacity*2*7*7)
        self.conv2 = nn.ConvTranspose2d(in_channels=capacity*2,
out_channels=capacity, kernel_size=4, stride=2, padding=1)
        self.conv1 = nn.ConvTranspose2d(in_channels=capacity,
out_channels=1, kernel_size=4, stride=2, padding=1)

    def forward(self, x):
        x = self.fc(x)
        x = x.view(x.size(0), capacity*2, 7, 7)
        x = F.relu(self.conv2(x))
        x = torch.sigmoid(self.conv1(x))
        return x


class ImprovedVariationalAutoencoder(VariationalAutoencoder):
    def __init__(self):
        super(ImprovedVariationalAutoencoder, self).__init__()
        self.encoder = ImprovedEncoder()
        self.decoder = ImprovedDecoder()

def vae_loss(recon_x, x, mu, logvar, variational_beta):
    recon_loss = F.binary_cross_entropy(recon_x.view(-1, 784),
x.view(-1, 784), reduction='sum')
    kldivergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) -
logvar.exp())
    return recon_loss + variational_beta * kldivergence

device = torch.device("cuda:0" if use_gpu and
```

```
torch.cuda.is_available() else "cpu")

improved_vae = ImprovedVariationalAutoencoder().to(device)
optimizer = torch.optim.Adam(params=improved_vae.parameters(),
lr=learning_rate, weight_decay=1e-5)

# Increase the weight of the KL-Divergence term
improved_variational_beta = 5

# Train the improved VAE
improved_vae.train()
improved_train_loss_avg = []

for epoch in range(num_epochs):
    improved_train_loss_avg.append(0)
    num_batches = 0

    for image_batch, _ in train_dataloader:
        image_batch = image_batch.to(device)
        recon_images, mu, logvar = improved_vae(image_batch)
        loss = vae_loss(recon_images, image_batch, mu, logvar,
improved_variational_beta)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        improved_train_loss_avg[-1] += loss.item()
        num_batches += 1

    improved_train_loss_avg[-1] /= num_batches
    print('Epoch [%d / %d] average reconstruction error: %f' %
(epoch+1, num_epochs, improved_train_loss_avg[-1]))

Epoch [1 / 100] average reconstruction error: 25253.535410
Epoch [2 / 100] average reconstruction error: 22958.545497
Epoch [3 / 100] average reconstruction error: 22749.205701
Epoch [4 / 100] average reconstruction error: 22606.104140
Epoch [5 / 100] average reconstruction error: 22515.817210
Epoch [6 / 100] average reconstruction error: 22429.496764
Epoch [7 / 100] average reconstruction error: 22376.673782
Epoch [8 / 100] average reconstruction error: 22324.111934
Epoch [9 / 100] average reconstruction error: 22280.463420
Epoch [10 / 100] average reconstruction error: 22247.358226
Epoch [11 / 100] average reconstruction error: 22216.371952
Epoch [12 / 100] average reconstruction error: 22181.732730
Epoch [13 / 100] average reconstruction error: 22152.300086
Epoch [14 / 100] average reconstruction error: 22136.184722
Epoch [15 / 100] average reconstruction error: 22112.018024
Epoch [16 / 100] average reconstruction error: 22088.954616
```

```
Epoch [17 / 100] average reconstruction error: 22073.615205
Epoch [18 / 100] average reconstruction error: 22057.352851
Epoch [19 / 100] average reconstruction error: 22035.406606
Epoch [20 / 100] average reconstruction error: 22034.240322
Epoch [21 / 100] average reconstruction error: 22007.903518
Epoch [22 / 100] average reconstruction error: 22006.655251
Epoch [23 / 100] average reconstruction error: 21984.563345
Epoch [24 / 100] average reconstruction error: 21977.278481
Epoch [25 / 100] average reconstruction error: 21963.715160
Epoch [26 / 100] average reconstruction error: 21952.722140
Epoch [27 / 100] average reconstruction error: 21939.012768
Epoch [28 / 100] average reconstruction error: 21931.685139
Epoch [29 / 100] average reconstruction error: 21923.076663
Epoch [30 / 100] average reconstruction error: 21907.774141
Epoch [31 / 100] average reconstruction error: 21908.677893
Epoch [32 / 100] average reconstruction error: 21895.686371
Epoch [33 / 100] average reconstruction error: 21899.258545
Epoch [34 / 100] average reconstruction error: 21860.922820
Epoch [35 / 100] average reconstruction error: 21875.796717
Epoch [36 / 100] average reconstruction error: 21866.331590
Epoch [37 / 100] average reconstruction error: 21846.762881
Epoch [38 / 100] average reconstruction error: 21842.141652
Epoch [39 / 100] average reconstruction error: 21839.777146
Epoch [40 / 100] average reconstruction error: 21835.062079
Epoch [41 / 100] average reconstruction error: 21830.755734
Epoch [42 / 100] average reconstruction error: 21813.988502
Epoch [43 / 100] average reconstruction error: 21810.605069
Epoch [44 / 100] average reconstruction error: 21804.591801
Epoch [45 / 100] average reconstruction error: 21810.274903
Epoch [46 / 100] average reconstruction error: 21792.485724
Epoch [47 / 100] average reconstruction error: 21800.891581
Epoch [48 / 100] average reconstruction error: 21785.138014
Epoch [49 / 100] average reconstruction error: 21791.454526
Epoch [50 / 100] average reconstruction error: 21773.852220
Epoch [51 / 100] average reconstruction error: 21778.379952
Epoch [52 / 100] average reconstruction error: 21767.762620
Epoch [53 / 100] average reconstruction error: 21771.605681
Epoch [54 / 100] average reconstruction error: 21776.646026
Epoch [55 / 100] average reconstruction error: 21744.274637
Epoch [56 / 100] average reconstruction error: 21753.521851
Epoch [57 / 100] average reconstruction error: 21743.558883
Epoch [58 / 100] average reconstruction error: 21748.396620
Epoch [59 / 100] average reconstruction error: 21729.768732
Epoch [60 / 100] average reconstruction error: 21727.806303
Epoch [61 / 100] average reconstruction error: 21740.608309
Epoch [62 / 100] average reconstruction error: 21725.836745
Epoch [63 / 100] average reconstruction error: 21727.303796
Epoch [64 / 100] average reconstruction error: 21709.761027
Epoch [65 / 100] average reconstruction error: 21721.071805
Epoch [66 / 100] average reconstruction error: 21696.944696
```

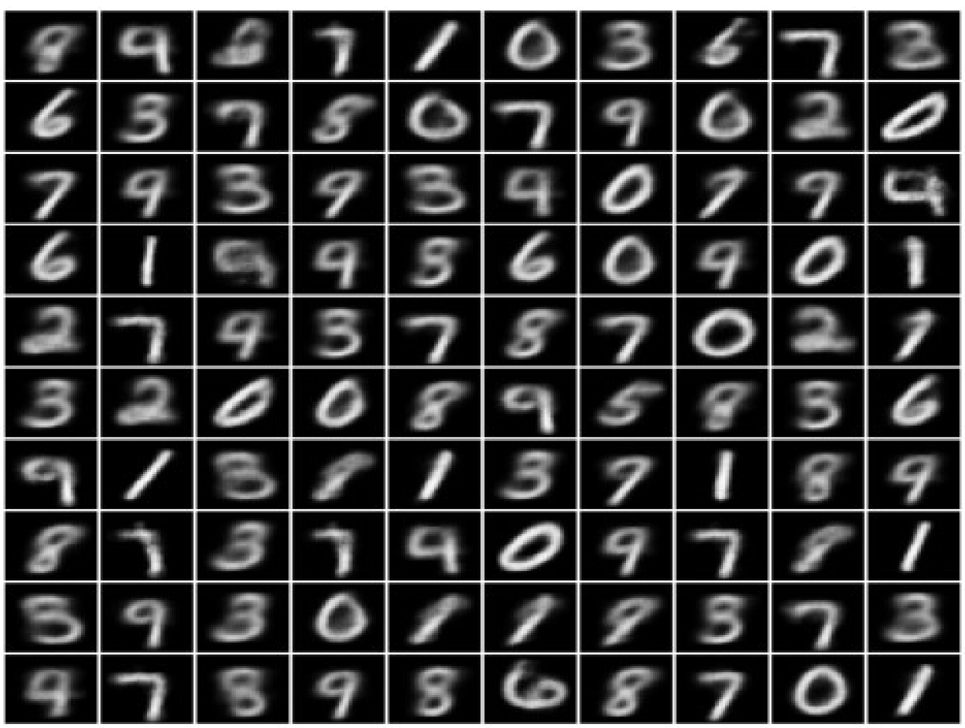
```
Epoch [67 / 100] average reconstruction error: 21706.107378
Epoch [68 / 100] average reconstruction error: 21701.416141
Epoch [69 / 100] average reconstruction error: 21707.399477
Epoch [70 / 100] average reconstruction error: 21708.259432
Epoch [71 / 100] average reconstruction error: 21689.845553
Epoch [72 / 100] average reconstruction error: 21694.574993
Epoch [73 / 100] average reconstruction error: 21685.029742
Epoch [74 / 100] average reconstruction error: 21682.874317
Epoch [75 / 100] average reconstruction error: 21667.784198
Epoch [76 / 100] average reconstruction error: 21677.307067
Epoch [77 / 100] average reconstruction error: 21681.967057
Epoch [78 / 100] average reconstruction error: 21663.101054
Epoch [79 / 100] average reconstruction error: 21653.238610
Epoch [80 / 100] average reconstruction error: 21661.060432
Epoch [81 / 100] average reconstruction error: 21671.052799
Epoch [82 / 100] average reconstruction error: 21667.019254
Epoch [83 / 100] average reconstruction error: 21668.394648
Epoch [84 / 100] average reconstruction error: 21644.628850
Epoch [85 / 100] average reconstruction error: 21653.779668
Epoch [86 / 100] average reconstruction error: 21650.517999
Epoch [87 / 100] average reconstruction error: 21644.477100
Epoch [88 / 100] average reconstruction error: 21640.777985
Epoch [89 / 100] average reconstruction error: 21637.374606
Epoch [90 / 100] average reconstruction error: 21641.164546
Epoch [91 / 100] average reconstruction error: 21640.060264
Epoch [92 / 100] average reconstruction error: 21632.306578
Epoch [93 / 100] average reconstruction error: 21619.238177
Epoch [94 / 100] average reconstruction error: 21631.690515
Epoch [95 / 100] average reconstruction error: 21622.439763
Epoch [96 / 100] average reconstruction error: 21626.256438
Epoch [97 / 100] average reconstruction error: 21623.346165
Epoch [98 / 100] average reconstruction error: 21612.472007
Epoch [99 / 100] average reconstruction error: 21607.092413
Epoch [100 / 100] average reconstruction error: 21612.837991
```

```
improved_vae.eval()

improved_test_loss_avg = 0
num_batches = 0

for image_batch, _ in test_dataloader:
    image_batch = image_batch.to(device)
    recon_images, mu, logvar = improved_vae(image_batch)
    loss = vae_loss(recon_images, image_batch, mu, logvar,
improved_variational_beta)

    improved_test_loss_avg += loss.item()
    num_batches += 1

improved_test_loss_avg /= num_batches
```

```
print('Improved VAE average reconstruction error: %f' %
(improved_test_loss_avg))
```

```
Improved VAE average reconstruction error: 20907.629126
```

```
import torchvision
import numpy as np
import matplotlib.pyplot as plt
plt.ion()

import torchvision.utils

improved_vae.eval()

with torch.no_grad():
    latent_dim = improved_vae.encoder.fc_mu.out_features
    random_latent_vectors = torch.randn(100, latent_dim).to(device)
    generated_images = improved_vae.decoder(random_latent_vectors)
    generated_images = generated_images.clamp(0, 1)
    generated_grid =
torchvision.utils.make_grid(generated_images.cpu(), nrow=10,
padding=1, pad_value=1)
    np_generated_grid = generated_grid.numpy().transpose((1, 2, 0))
    plt.imshow(np_generated_grid, cmap='gray', aspect='auto')
    plt.axis('off')
    plt.show()
```



I have increased the weight of the KL-divergence term (*variational_beta*) which should encourage the model to ensure the learned latent distribution aligns more closely with a unit Gaussian, potentially improving the quality of generated samples. The quality is improved and the each image digits are not as blurry as before. For instance with the previous VAE architecture, the digit 6 and 5 were confused to be as 8, however, in this improvised version the digits 5, 6 and 8 are clear than before.