Assignment 4 - Variational Autoencoders

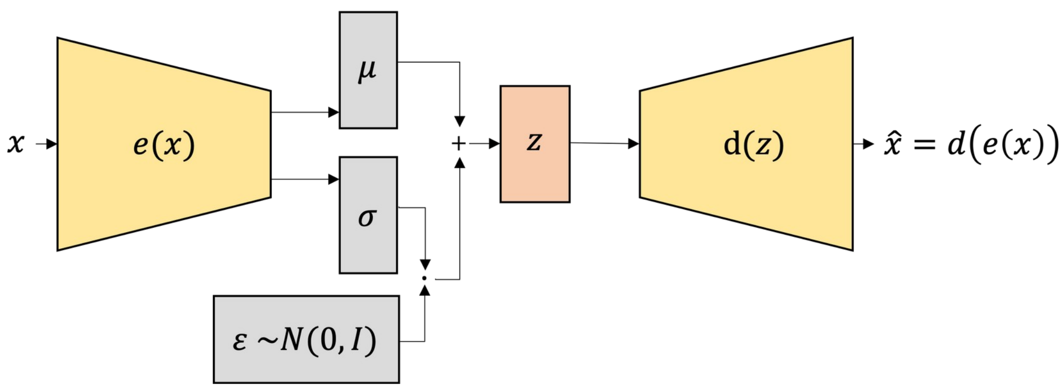
In this assignment, we will train a model to produce new human faces with variational autoencoders (VAEs). Variational autoencoders let us design complex generative models of data, and fit them to large datasets. They can generate images of fictional celebrity faces (as we'll do in this assignment), high-resolution digital artwork and many more tasks. These models also yield state-of-the-art machine learning results in image generation and reinforcement learning. Variational autoencoders (VAEs) were defined in 2013 by Kingma and Wellings [1].

In this assignment, you will build, train and analyze a VAE with the CelebA dataset. You will analyze how well images can be reconstructed from the lower dimensional representations and try to generate images that look similar to the images in the CelebA dataset.

[1] Kingma, Diederik P., and Max Welling. "Auto-encoding variational bayes." arXiv preprint arXiv:1312.6114 (2013).

Section 1: Variational Autoencoders

Let us recall the structure of the variational autoencoder:



Imports

Before we begin, we import the needed libraries.

You may modify the starter code as you see fit, including changing the signatures of functions and adding/removing helper functions. However, please make sure that we can understand what you are doing and why.

```
from torchvision import datasets
from torchvision import transforms
from torch.autograd import Variable
import torch
import torch.nn as nn
import torch.nn.functional as nnF
```

```
from torchvision.utils import make_grid
import torch.utils.data as data_utils
from IPython.display import Image
import matplotlib.pyplot as plt
import numpy as np
import random
import torchvision.transforms.functional as F
from torchvision.utils import make_grid
import os
import zipfile
from torch.nn.modules import KLDivLoss

%pip install wget
import wget

# use GPU for computation if possible: Go to RUNTIME -> CHANGE RUNTIME
TYPE -> GPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting wget
  Downloading wget-3.2.zip (10 kB)
  Preparing metadata (setup.py) ... e=wget-3.2-py3-none-any.whl
size=9674
sha256=b07744279a77bf29850d8fc67e6959830f04318a4b0d84237ecd51a53122caf
4
  Stored in directory:
/root/.cache/pip/wheels/bd/a8/c3/3cf2c14a1837a4e04bd98631724e81f33f462
d86a1d895fae0
Successfully built wget
Installing collected packages: wget
Successfully installed wget-3.2
```

Connect to your Google Drive, select the path in your drive for saving the checkpoints of your model, which we will train later.

```
from google.colab import drive
drive.mount('/content/gdrive')

# Path to save the dataset.
PATH_TO_SAVE_MODEL = '/content/gdrive/MyDrive/Colab
Notebooks/assignment4/' # TODO - UPDATE ME!
```

```
Mounted at /content/gdrive
```

Define random seeds in order to reproduce your results.

```
# TO DO: Set random seeds - to your choice
# to make r.v. determinstic
```

```
torch.manual_seed(100)          # Insert any integer
torch.cuda.manual_seed(100)     # Insert any integer
```

Question 1. Basic Principles (10 %)

Part (a) -- 3%

What is the difference between deterministic autoencoder we saw in class and the variational autoencoder?

Our Answer

Deterministic autoencoders, as we saw in class, fix the latent vector z to a deterministic mapping of the input y. This way, our network has to learn a relatively large vector.

Variational autoencoders aim to reduce the dimentionality of the latent the network needs to learn. It does that by allowing stochastic mapping, meaning a gaussian noise is added to the input. We than force the output distribution that the network is learning to be as close as possible to the Standard Normal Diviation $N(0,1)$.

Part (b) -- 3%

In which manner Variational Autoencoder is trained? Explain.

Our Answer

To get the loss function, due to the approximation to the standard normal diviation our latent is simply $z=\mu+\sigma\odot\epsilon$, where $\epsilon\sim N(0,1)$. This way we only need to train μ and σ and don't use regular backpropagation.

It is possible to get better results if we balance the ELBO. We manage that by adding a hyperparemeter β such that: $L(\phi,\theta)=\beta\cdot D_{KL}¿$

Part (c) -- 4%

In class we saw another generative model, known as generative adversarial network (GAN). What are the differences in terms of task objective between GANs and VAEs? Give an example for a task which a VAE is more suitable than GAN, and vice versa.

Our Answer

VAEs and GANs differ in how they are trained. VAEs use an unsupervised approach with a stochastic latent vector, while GANs use a supervised technique with an adversary neural network.

Because they learn from existing data, and especially when adding the hyperparemeter β as noted above, VAEs are better at generating new information such as people's faces. It learns the features of the image (such as "nose", "eyes" and "skin color"), and is able to create new ones that are combinations of data learned from several inputs (the new nose is now 10% this and 90% that, with this skin tone).

Because they need to "cheat" the adversary, GANs are very good at creating specifically what the user asked for. This is why they can be used for, for example, text-to-image generators.

In reality, VAEs and GANs will pften be used togather, for example this way we can generate new images and make the resolution much higher.

Question 2. Data (15 %)

In this assignement we are using the CelebFaces Attributes Dataset (CelebA).

The CelebA dataset, as its name suggests, is comprised of celebrity faces. The images cover large pose variations, background clutter, diverse people, supported by a large quantity of images and rich annotations. This data was originally collected by researchers at MMLAB, The Chinese University of Hong Kong.

Overall

- 202,599 number of face images of various celebrities
- 10,177 unique identities, but names of identities are not given
- 40 binary attribute annotations per image
- 5 landmark locations

In this torchvision version of the dataset, each image is in the shape of $[218,178,3]$ and the values are in $[0,1]$.

Here, you will download the dataset to the Google Colab disk. It is highly recommended not to download the dataset to your own Google Drive account since it is time consuming.

```
data_path = "data" ## TO DO -- UPDATE ME!
# Path to folder with the dataset
dataset_folder = f"{data_path}/celeba"
os.makedirs(dataset_folder, exist_ok=True)

base_url = "https://graal.ift.ulaval.ca/public/celeba/"

file_list = [
    "img_align_celeba.zip",
    "list_attr_celeba.txt",
    "identity_CelebA.txt",
    "list_bbox_celeba.txt",
    "list_landmarks_align_celeba.txt",
    "list_eval_partition.txt",
]

for file in file_list:
    url = f"{base_url}/{file}"
    if not os.path.exists(f"{dataset_folder}/{file}"):
        wget.download(url, f"{dataset_folder}/{file}")
```

```
with zipfile.ZipFile(f"{dataset_folder}/img_align_celeba.zip", "r") as
ziphandler:
    ziphandler.extractall(dataset_folder)
```

Part (a) -- 5%

Apply transformations:

The data is given as PIL (Python Imageing Library) images. Since we are working with PyTorch, we wish to apply transformations to the data in order to process it properly.

Here you should apply transformations to the data. There are many kinds of transformations which can be found here: https://pytorch.org/vision/stable/transforms.html. Note that transformations can be chained together using Compose method.

Think which transformations can be suitable for this task and apply it in the form of:

trfm = transforms.Compose([transforms.transform1(),transforms.transform2(),...])

We recommend to consider:

- transforms.ToTensor()
- transforms.Resize()

```
width = 178
height = 218
trfm = transforms.Compose([
    transforms.ToTensor(),
    transforms.Resize(size=(height,width))
])

training_data = datasets.CelebA(root=data_path, split='train',
download=False, transform=trfm) #load the dataset (without download it
directly) from our root directory on google drive disk.
test_data = datasets.CelebA(root=data_path, split='test',
download=False, transform=trfm)
```

Part (b) -- 5%

In order to get in touch with the dataset, and to see what we are dealing with (which is always recommended), we wish to visualize some data samples from the CelebA dataset.

Write a function: show():

INPUT: Python list of length 32 where each element is an image, randomly selected from the training data.

OUTOUT: Showing a 8X4 grid of images.

```
def show(imgs):
    fig, axs = plt.subplots(8, 4, figsize=(16, 20))
    for i in range(8):
```

```python
        for j in range(4):
            axs[i, j].imshow(imgs[4*i + j])
            axs[i, j].axis('off')
    plt.show()
    return None

num_images = len(training_data)
indices = random.sample(range(num_images), 32)
imgs = [training_data[i][0].permute(1,2,0) for i in indices]
show(imgs)
```

Extrapolate in the image domain:

Part (c) -- 5%

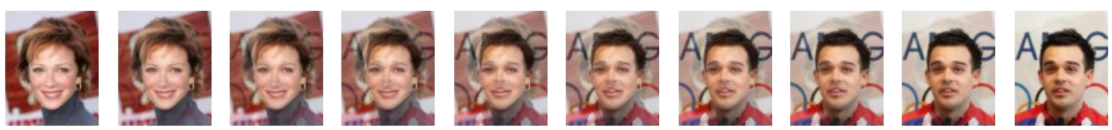
Extrapolate in the image domain:

Here, randomly take 2 images from the training dataset, combine them together and plot the result. For example, consider X_1 and X_2 to be 2 images randomly taken from the training data. Plot $\alpha \cdot X_1 + (1-\alpha) \cdot X_2$.

Explain the results, is extrapolation in the image domain reasonable?

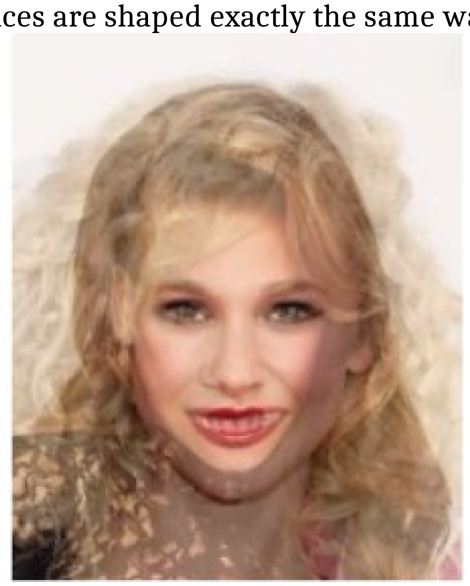
Note: Recall that the images should be in the $[0,1]$ interval.

```
indices = random.sample(range(len(training_data)), 2)
img1, img2 = [training_data[i][0].permute(1,2,0) for i in indices]
fig = plt.figure(figsize=(16, 20))
for i in range(10):
  alpha = i / 10
  fig.add_subplot(1, 11, i+1)
  img = alpha*img1 + (1-alpha)*img2
  plt.imshow(img)
  plt.axis('off')
```



Our Answer

Extrapulating in this manner in the image domain makes ammusing results, but not very useful ones. Since not all images were taken in exactly the same way, and not all human's faces are shaped exactly the same way, we will inevitably get results like this one:



We can see both faces in this mushed-togather image. While in this case the facial features almost align, we still clearly see, for example, two mouths stacked one on top of the other. This is not the desired result when we try to emulate new human faces.

Question 3. VAE Foundations (15 %)

Let us start by recalling the analytical derivation of the VAE.

The simplest version of VAE is comprised of an encoder-decoder architecture. The *encoder* is a neural network which its input is a datapoint x, its output is a hidden representation z, and it has weights and biases θ. We denote the encoder's mapping by $P_\theta(z \vee x)$. The *decoder* is another neural network which its input is the data sample z, its output is the reconstructed input x, and its parameters ϕ. Hence, we denote the decoder's mapping by $P_\phi(x \vee z)$.

The goal is to determine a posterior distribution $P_\theta(z \vee x)$ of a latent variable z given some data evidence x. However, determining this posterior distribution is typically computationally intractable, because according to Bayes:

$$(1)\ P(z \vee x) = \frac{P(x \vee z)\, P(z)}{P(x)}$$

The term $P(x)$ is called the evidence, and we can calculate it by marginalization on the latent variable:

$$P(x) = \int_z P(x \vee z)\, P(z)\, dz$$

Unfortunately, this term is intractable because it requires computation of the integral over the entire latent space z. To bypass this intractability problem we approximate the posterior distribution with some other distribution $q(z \vee x_i)$. This approximation is made by the KL-divergence:

$(2)\ D_{KL}$ ¿

Applying Bayes' theorem to the above equation yields,

$(3)\ D_{KL}$ ¿

This can be broken down using laws of logarithms, yielding,

$$(4)\ -\int_z q(z \vee x_i) \cdot \left[\log\left(\frac{P(x_i \vee z)\, P(z)}{q(z \vee x_i)}\right) - \log\left(P(x_i)\right)\right] dz \geq 0$$

Distributing the integrand then yields,

$$(5)\ -\int_z q(z \vee x_i) \cdot \log\left(\frac{P(x_i \vee z)\, P(z)}{q(z \vee x_i)}\right) dz + \int_z q(z \vee x_i) \log\left(P(x_i)\right) dz \geq 0$$

In the above, we note that $log(P(x))$ is a constant and can therefore be pulled out of the second integral above, yielding,

$$(6) - \int_z q(z \vee x_i) \cdot \log\left(\frac{P(x_i \vee z) P(z)}{q(z \vee x_i)}\right) dz + \log(P(x_i)) \int_z q(z \vee x_i) dz \geq 0$$

And since $q(z \vee x_i)$ is a probability distribution it integrates to 1 in the above equation, yielding,

$$(7) - \int_z q(z \vee x_i) \cdot \log\left(\frac{P(x_i \vee z) P(z)}{q(z \vee x_i)}\right) dz + \log(P(x_i)) \geq 0$$

Then carrying the integral over to the other side of the inequality, we get,

$$(8) \log(P(x_i)) \geq \int_z q(z \vee x_i) \cdot \log\left(\frac{P(x_i \vee z) P(z)}{q(z \vee x_i)}\right) dz$$

From Equation (8) it follows that:

$$(9) \log(P(x_i)) \geq \int_z q(z \vee x_i) \cdot \log\left(\frac{P(z)}{q(z \vee x_i)}\right) dz + \int_z q(z \vee x_i) \cdot \log(P(x_i \vee z)) dz$$

Which is equivalent to:

$$(10) \log(P(x_i)) \geq -D_{KL} ¿$$

The right hand side of the above equation is the Evidence Lower BOund (ELBO). Its bounds $\log(P(x))$ which is the term we seek to maximize. Therefore, maximizing the ELBO maximizes the log probability of our data.

Part (a) -- 5%

A we see above, the $ELBO = -D_{KL} ¿$ is comprised of 2 terms. Explain the meaning of each one of them in terms of a loss function.

Our Answer

The first term, $D_{KL}[q(z|x_i)||P(z)]$ is the KL divergence between the approximating distribution $q(z|x_i)$ and the true probability $P(z)$.

When we try to minimize the KL divergence, we encourage $q(z|x_i)$ to be similar to $P(z)$, hence this term serves as a regularization term.

The second term, $E_{q(z|x_i)}[log(P(x_i|z))]$, is the expected log likelihood of the data under the approximating distribution. This term encourages the approximating distribution to assign high probability to data points that are likely under the model, acting as the reconstruction loss in our model.

Part (b) -- 10%

As we saw in class, in traditional variational autoencoder we assume:

$$P(z) \sim N(\mu_p, \sigma_p^2) = \frac{1}{\sqrt{2\pi\sigma_p^2}} \exp\left(-\frac{(z-\mu_p)^2}{2\sigma_p^2}\right)$$

and

$$q(z \vee x) \sim N(\mu_q, \sigma_q^2) = \frac{1}{\sqrt{2\pi\sigma_q^2}} \exp\left(-\frac{(z-\mu_q)^2}{2\sigma_q^2}\right)$$

Assume $\mu_p = 0$ and $\sigma_p^2 = 1$. Show that:

$ -D_{KL}\big(q(z|x_i)||P(z)\big) = \frac{1}{2}\big[1+\log(\sigma_{q}^2)-\sigma_{q}^2-\mu_q^2\big]$

Our Answer

The KL Divergence:

$$-D_{KL}(q(z|x_i)||P(z)) = -\int_{-\infty}^{\infty} q(z|x_i) \cdot log(\frac{q(z|x_i)}{P(z)})dz$$

Using logarithmic rules:

$$= \int_{-\infty}^{\infty} q(z|x_i) \cdot log(P(z))dz - \int_{-\infty}^{\infty} q(z|x_i) \cdot log(q(z|x_i))dz$$

1) Since integration is done over all the real line, we know:

$$-\int_{-\infty}^{\infty} q(z|x_i) \cdot log(q(z|x_i))dz = \frac{1}{2}(1 + log(2\pi\sigma_q^2)) = \frac{1}{2}(1 + log(2\pi) + log(\sigma_q^2))$$

2) As we showed in class, and since we assume $\mu_p = 0$ and $\sigma_p^2 = 1$ we can write:

$$\int_{-\infty}^{\infty} q(z|x_i) \cdot log(P(z))dz = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma_q^2}}\exp(-\frac{(z-\mu_q)^2}{2\sigma_q^2}) \cdot log(\frac{1}{\sqrt{2\pi}}\exp(-\frac{z^2}{2}))dz$$

Apply log rules again:

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma_q^2}}\exp(-\frac{(z-\mu_q)^2}{2\sigma_q^2}) \cdot (log(1) - log(\sqrt{2\pi}) + log(\exp(-\frac{z^2}{2})))dz =$$

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma_q^2}}\exp(-\frac{(z-\mu_q)^2}{2\sigma_q^2}) \cdot (-\frac{log(2\pi)}{2} - \frac{z^2}{2})dz$$

Since $\frac{log(2\pi)}{2}$ is multiplied by the entire distribution, and isn't a function of z, we can write:

$$= -\frac{log(2\pi)}{2} - \frac{1}{2}\int_{-\infty}^{\infty} z^2 \cdot \frac{1}{\sqrt{2\pi\sigma_q^2}}\exp(-\frac{(z-\mu_q)^2}{2\sigma_q^2})dz$$

Under the integral we recognize the second moment, hence:

$$= -\frac{1}{2}(log(2\pi) + \sigma_q^2 + \mu_q^2)$$

3) We combine (1) and (2):

$$-D_{KL}(q(z|x_i)||P(z)) = \frac{1}{2}(1 + log(2\pi) + log(\sigma_q^2)) - \frac{1}{2}(log(2\pi) + \sigma_q^2 + \mu_q^2) = \frac{1}{2}[1 + \log(\sigma_q^2) - \sigma_q^2 - \mu_q^2]$$

Minimizing the loss function, over a batch in the dataset now can be written as:

$$L(\theta, \phi) = -\sum_{j}^{J}\left(\frac{1}{2}\left[1 + \log(\sigma_{q_j}^2) - \sigma_{q_j}^2 - \mu_{q_j}^2\right]\right) - \frac{1}{M}\sum_{i}^{M}\left(E_{q_\theta(z \vee x_i)}\left[\log(P_\phi(x_i \vee z))\right]\right)$$

where J is the dimension of the latent vector z and M is the number of samples stochastically drawn from the dataset.

Question 4. VAE Implementation (25 %)

As seen in class, a suitable way to extract features from dataset of images is by convolutional neural network (CNN). Hence, here you will build a convolutional VAE. The basic idea is to start from full resolution images, and by convolutional kernels extract the important features of the dataset. Remember that the output of the VAE should be in the same dimensions (H_1, W_1, C_1) as the input images.

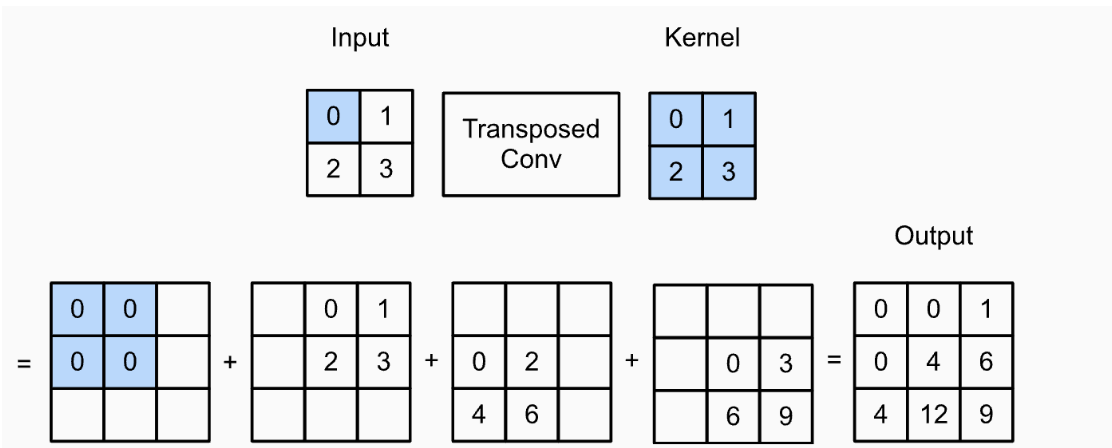
The encoder should be comprised of convolutional layers (nn.Conv2d). Recall that the dimension of the input images is changing according to:

$$Z=\left(H_2\left(\text{¿}\frac{H_1-F+2P}{S}+1\right),W_2\left(\text{¿}\frac{W_1-F+2P}{S}+1\right),C_2\right)$$

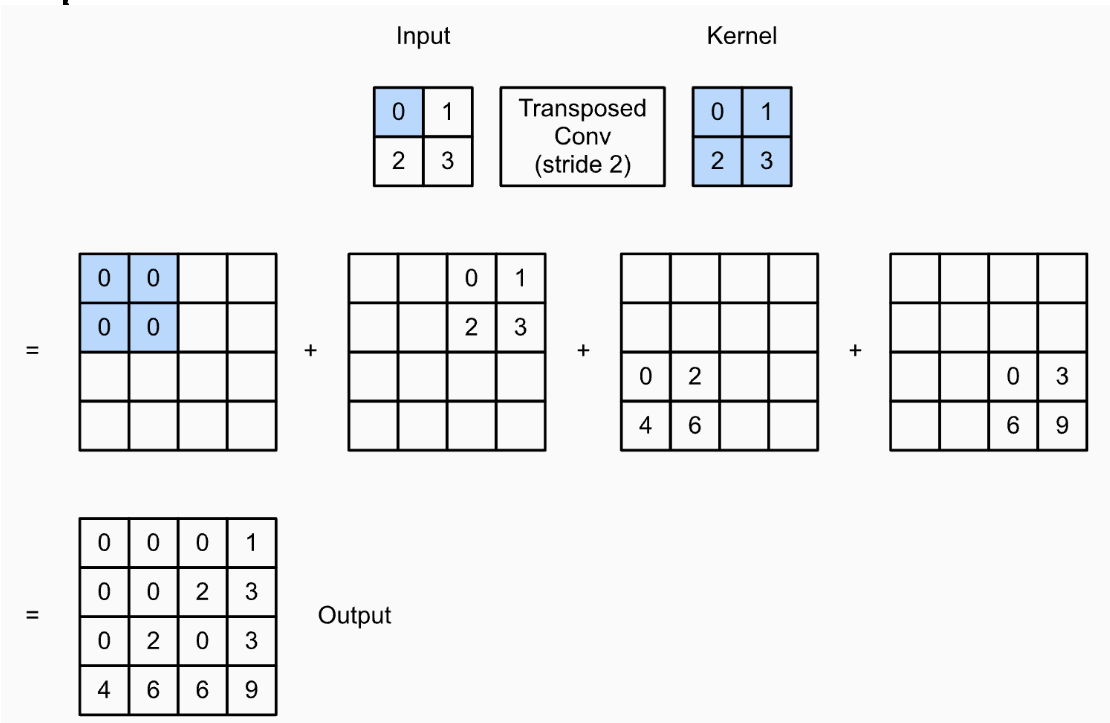
where S is the stride, F is the kernel size, P is the zero padding and C_2 is the selected output channels. Z is the output image.

The decoder should reconstruct the images from the latent space. In order to enlarge dimensions of images, your network should be comprised of transposed convolutional layers (nn.ConvTranspose2d). See the following images of the operation of transpose convolution to better understand the way it works.

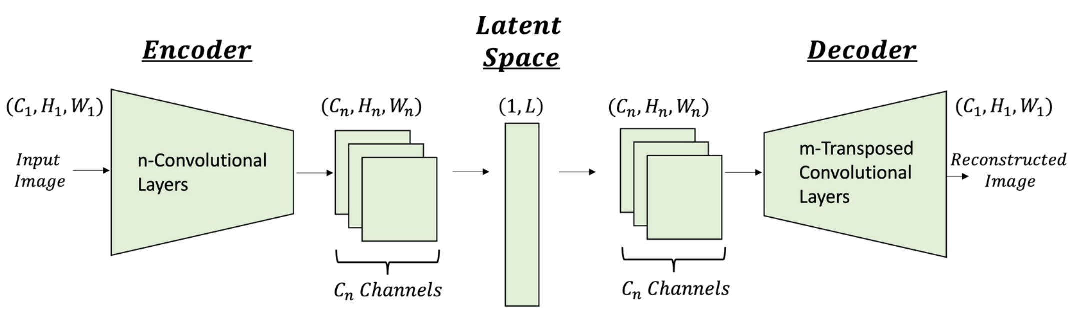
Transposed Convolution with Stride = 1



Transposed Convolution with Stride = 2



The architecture of your VAE network should be in the following form:



Part (a) -- 7%

Encoder

Here, you will implement the architecture of the encoder.

The encoder should consist of 4 Blocks as follows:

BLOCK 1:

- Convolutional layer (nn.Conv2D(in_channels, num_hidden, kernel_size=(3,3), stride=(2,2)))
- Batch Normalization(num_hidden)
- Activation Function: nn.ReLU()

BLOCK 2:

- Convolutional layer (nn.Conv2D(num_hidden, num_hidden * 2, kernel_size=(3,3), stride=(2,2))
- Batch Normalization(num_hidden * 2)
- Activation Function: nn.ReLU()

BLOCK 3:

- Convolutional layer (nn.Conv2D(num_hidden * 2, num_hidden * 4, kernel_size=(3,3), stride=(2,2))
- Batch Normalization(num_hidden * 4)
- Activation Function: nn.ReLU()

BLOCK 4:

- Convolutional layer (nn.Conv2D(num_hidden * 4, num_hidden * 8, kernel_size=(3,3), stride=(2,2))
- Batch Normalization(num_hidden * 8)
- Activation Function: nn.ReLU()

In addidion to the 4 Blocks, you should add the following linear layers:

Linear μ:

- nn.Linear(___ ,latent).

Linear $\log(\sigma)$:

- nn.Linear(___ ,latent).

NOTES:

- The input of the linear layer should be according to the size of the images you picked in the transformation part. (If you did resize the images)

- Consider using Padding in the convolutional layers to correct mismatches in sizes.

- In the forward function, you will have to reshape the output from the 4'th block to $(H_4 \cdot W_4 \cdot C_4, latent)$, where H_4 is the height of the output image from the 4'th block, W_4 is the width of the output image from the 4'th block and C_4 is num_hidden*8 (number of channels of the output image from the 4'th block).

You can change any parameter of the network to suit your code - this is only a recommendation.

```
class Encoder(nn.Module):
    def __init__(self, in_channels, num_hiddens, latent, width,
height):
        super(Encoder, self).__init__()
        # YOUR CODE GOES HERE:
        reduce_W = (1+(1+(1+(1+width)//2)//2)//2)//2
```

```
        reduce_H = (1+(1+(1+(1+height)//2)//2)//2)//2
        self.reduce_size = 8*num_hiddens*reduce_W*reduce_H
        self.num_hiddens = num_hiddens
        self.latent = latent
        self.block1 = nn.Sequential(nn.Conv2d(in_channels,
num_hiddens, kernel_size=(3,3), stride=(2,2),padding=(1,1)),
                                    nn.BatchNorm2d(num_hiddens),
                                    nn.ReLU())

        self.block2 = nn.Sequential(nn.Conv2d(num_hiddens,
num_hiddens*2, kernel_size=(3,3), stride=(2,2),padding=(1,1)),
                                    nn.BatchNorm2d(num_hiddens*2),
                                    nn.ReLU())

        self.block3 = nn.Sequential(nn.Conv2d(num_hiddens*2,
num_hiddens*4, kernel_size=(3,3), stride=(2,2),padding=(1,1)),
                                    nn.BatchNorm2d(num_hiddens*4),
                                    nn.ReLU())

        self.block4 = nn.Sequential(nn.Conv2d(num_hiddens*4,
num_hiddens*8, kernel_size=(3,3), stride=(2,2),padding=(1,1)),
                                    nn.BatchNorm2d(num_hiddens*8),
                                    nn.ReLU())

        self.fc_mu =(nn.Linear(self.reduce_size,latent))
        self.fc_logvar =(nn.Linear(self.reduce_size,latent))

    def forward(self, inputs):
        # YOUR CODE GOES HERE:
        x = self.block1(inputs)
        x = self.block2(x)
        x = self.block3(x)
        x = self.block4(x)
        x = x.view(x.size(0), -1)
        mu = self.fc_mu(x)
        logvar = self.fc_logvar(x)

        return mu, logvar
```

Notice: We output $\log \sigma$ and not σ^2, this is a convention when training VAEs but it is completely equivalent.

Part (b) -- 7%

Decoder

Here, you will implement the architecture of the decoder.

First, Apply a linear layer to the input of the decoder as follows:

- nn.Linear(latent, ___).

The output of the linear layer should match to $H_4 \cdot W_4 \cdot C_4$, which were the same parameters from the encoder 4'th block's output.

Then, the decoder should consist of 4 Blocks as follows:

BLOCK 1:

- Transposed Convolutional layer (nn.ConvTranspose2d(in_channels, num_hidden // 2, kernel_size=(4,4), stride=(2,2)))
- Batch Normalization(num_hidden // 2)
- Activation Function: nn.ReLU() or nn.LeakyReLU()

BLOCK 2:

- Transposed Convolutional layer (nn.ConvTranspose2d(num_hidden // 2, num_hidden // 4, kernel_size=(4,4), stride=(2,2)))
- Batch Normalization(num_hidden // 4)
- Activation Function: nn.ReLU() or nn.LeakyReLU()

BLOCK 3:

- Transposed Convolutional layer (nn.ConvTranspose2d(num_hidden // 4, num_hidden // 8, kernel_size=(4,4), stride=(2,2)))
- Batch Normalization(num_hidden // 8)
- Activation Function: nn.ReLU() or nn.LeakyReLU()

BLOCK 4:

- Transposed Convolutional layer (nn.ConvTranspose2d(num_hidden // 8, num_hidden // 8, kernel_size=(4,4), stride=(2,2)))
- Batch Normalization(num_hidden // 8)
- Activation Function: nn.ReLU() or nn.LeakyReLU()

Afterwards, we should generate an image in the same size as our input images. Thus add 1 more block consisting of:

BLOCK 5:

- nn.Conv2d(num_hiddens//8, out_channels=3,kernel_size=(3,3), stride=(1,1), padding=(1,1)),
- Activation function.

NOTES:

- The output of the linear layer should be according to the size of the images you picked in the transformation part. (If you did resize the images)

- Consider using Padding in the transposed convolutional layers to correct mismatches in sizes.

- In the forward function, you will have to reshape the output of the linear layer to ($Batch, H_4, W_4, C_4$)
- The output of the decoder should be of values in $[0,1]$.

You can change any parameter of the network to suit your code, this is only a recommendation.

```
class Decoder(nn.Module):
    def __init__(self, in_channels, num_hiddens,latent, width,
height):
        super(Decoder, self).__init__()
        # YOUR CODE GOES HERE:
        self.num_hiddens = num_hiddens
        self.reduce_W = (1+(1+(1+(1+width)//2)//2)//2)//2
        self.reduce_H = (1+(1+(1+(1+height)//2)//2)//2)//2
        self.fc_dec = nn.Linear(latent,num_hiddens*14*12) # Insert the
output size

        self.block1 = nn.Sequential(nn.ConvTranspose2d(in_channels,
num_hiddens // 2, kernel_size=(4,4), stride=(2,2),padding=(1,1)),
                                    nn.BatchNorm2d(num_hiddens // 2),
                                    nn.LeakyReLU())

        self.block2 = nn.Sequential(nn.ConvTranspose2d(num_hiddens //
2, num_hiddens // 4, kernel_size=(4,4), stride=(2,2),padding=(2,2)),
                                    nn.BatchNorm2d(num_hiddens // 4),
                                    nn.LeakyReLU())

        self.block3 = nn.Sequential(nn.ConvTranspose2d(num_hiddens //
4, num_hiddens // 8, kernel_size=(4,4), stride=(2,2),padding=(0,2)),
                                    nn.BatchNorm2d(num_hiddens // 8),
                                    nn.LeakyReLU())

        self.block4 = nn.Sequential(nn.ConvTranspose2d(num_hiddens //
8, num_hiddens // 8, kernel_size=(4,4), stride=(2,2),padding=(2,2)),
                                    nn.BatchNorm2d(num_hiddens // 8),
                                    nn.LeakyReLU())

        self.block5 = nn.Sequential(nn.Conv2d(num_hiddens//8,
out_channels=3,kernel_size=(3,3), stride=(1,1), padding=(1,1)),
                                    nn.Sigmoid()) # Add convolution
layer and activation layer


    def forward(self, inputs):
        # YOUR CODE GOES HERE:
        x_rec = self.fc_dec(inputs)
        x_rec = x_rec.view(x_rec.size(0), self.num_hiddens,
self.reduce_H, self.reduce_W)
```

```
        x_rec = self.block1(x_rec)
        x_rec = self.block2(x_rec)
        x_rec = self.block3(x_rec)
        x_rec = self.block4(x_rec)
        x_rec = self.block5(x_rec)

        return x_rec
```

Part (c) -- 4%

VAE Model

Once you have the architecture of the encoder and the decoder, we want to put them together and train the network end-to-end.

Remember that in VAEs, you need to sample from a gaussian distribution at the input of the decoder. In order to backpropagate through the network, we use the reparametrization trick. The reparametrization trick is saying that sampling from $z \sim N(\mu, \sigma)$ is equivalent to sampling $\varepsilon \sim N(0,1)$ and setting $z = \mu + \sigma \odot \varepsilon$. Where, epsilon is an input to the network while keeping your sampling operation differentiable. The reparametrization function is given to you in the VAE class.

Here, you should write the *forward()* function and to combine all the model's settings to a final network.

```
class VAE(nn.Module):
    def __init__(self,
enc_in_chnl,enc_num_hidden,dec_in_chnl,dec_num_hidden,latent, width,
height):
        super(VAE, self).__init__()
        self.encode = Encoder(in_channels=enc_in_chnl,
num_hiddens=enc_num_hidden,latent = latent, width = width, height =
height)
        self.decode = Decoder(in_channels=dec_in_chnl,
num_hiddens=dec_num_hidden,latent = latent, width = width, height =
height)

    # Reparametrization Trick
    def reparametrize(self, mu, logvar):
      std = torch.exp(0.5 * logvar)
      eps = torch.randn_like(std)
      return eps.mul(std).add_(mu)

    # Initialize Weights
    def weight_init(self, mean, std):
        for m in self._modules:
            if isinstance(m, nn.ConvTranspose2d) or isinstance(m,
nn.Conv2d):
                m.weight.data.normal_(mean, std)
                m.bias.data.zero_()
```

```
    def forward(self, x):
        # YOUR CODE GOES HERE:
        mu, logvar = self.encode(x)
        z = self.reparametrize(mu, logvar)
        x_rec = self.decode(z)
        return x_rec, mu, logvar
```

Part (d) -- 7%

Loss Function

As we saw earlier, the loss function is based on the ELBO; Over a batch in the dataset, it can be written as:

$$L(\theta,\phi)=-\sum_{j}^{J}\left(\frac{1}{2}\left[1+\log\left(\sigma_{q_j}^2\right)-\sigma_{q_j}^2-\mu_{q_j}^2\right]\right)-\frac{1}{M}\sum_{i}^{M}\left(E_{q_\theta(z\vee x_i)}\left[\log\left(P_\phi\left(x_i\vee z\right)\right)\right]\right)$$

where J is the dimension of the latent vector z and M is the number of samples stochastically drawn from the dataset.

β-Variational Autoencoder (β-VAE)

As seen in class, the fact that the ELBO is comprised of the sum of two loss terms implies that these can be balanced using an additional hyperparameter β, i.e.,

$\beta \cdot D_{KL}$¿

It is highly recommended to use the β-loss for increasing performance.

Explain what could be the purpose of the hyperparameter β in the loss function? If $\beta=1$ is same as VAE, What is the effect of $\beta\neq1$?

Our Answer

When $\beta\neq1$ we can choose how much we want to emphasise to the regularization term in the loss function.

A higher value of beta places more emphasis on the regularization term, thus encouraging the latent space to have a more structured and informative representation of the input data. This results in a more disentangled and interpretable latent space but lower quality reconstruction.

A lower value of beta places less emphasis on the regularization term and results in a more accurate reconstruction, but the latent space becomes less structured and interpretable.

Here you should write specifically the code for the loss function.

```
beta = 0.1
mse = nn.MSELoss(reduction='sum')

def vae_loss(x_recon, x, mu, logvar):
```

```
    # YOUR CODE GOES HERE....
    # We used MSE to calculate the loss, not BCE as advised
    MSE = mse(x_recon, x)/(len(x_recon))
    KLD = -0.5 * torch.sum(1 + logvar - logvar.exp() -
mu.pow(2) ,dim=-1).mean(dim=0)

    return MSE, KLD*beta
```

Here, define all the hyperparameters values for the training process.

We gave you recommended values for the VAE model. You can modify and change it to suit your code better if needed.

```
learning_rate = 0.001
batch_size = 50
num_epochs = 25
dataset_size = 30000 # How many data samples to use for training,
30,000 should be enough.

#VAE Class inputs:
enc_in_chnl = 3
enc_num_hidden = 32
dec_in_chnl = 256
dec_num_hidden = 256

train_loader = torch.utils.data.DataLoader(training_data,
batch_size=batch_size, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_data,
batch_size=batch_size, shuffle=True)
```

Question 5. VAE Training (15 %)

Part (a) -- 4%

Complete the training function below

```
def train(num_epochs,batch_size,dataset_size,model):
    '''
    This is a starter code for the training process. You can modify it
for your
    own conveinient.
    num_epochs - number of training epochs
    batch_size - size of the batches
    dataset_size - How many training samples to use.
    model - The model you are training.

    Note: decide what are the outputs of the function.
    '''

    # Your code goes Here:
    torch.cuda.empty_cache()
```

```
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    test_iter = iter(test_loader)
    iters, train_loss, val_loss =[],[],[]

    for epoch in range(num_epochs):
        torch.cuda.empty_cache()
        print(f"Epoch {epoch}")
        model.train()
        for batch_idx, batch in enumerate(train_loader):
            img_test, _ = batch

            if torch.cuda.is_available():
                img_test = img_test.cuda()
            else:
                img_test = img_test.to(device)
            x_rec , mu, logvar = model(img_test)
            MSE, KLD = vae_loss(x_rec, img_test, mu, logvar)
            elbo = KLD + MSE

            optimizer.zero_grad()
            elbo.backward()
            optimizer.step()

            if batch_idx % 10 == 0:
                if batch_idx % 100 == 0:
                  print(f'TRAIN          Batch {batch_idx} ---- loss
average {(float(elbo)/len(img_test))}')

                train_loss.append((float(elbo)/len(img_test)))
                iters.append(batch_idx)

                with torch.no_grad():
                  model.eval()

                try:
                  img_val, label = next(test_iter)
                except StopIteration:
                  test_iter=iter(test_loader)
                  img_val, label = next(test_iter)

                if torch.cuda.is_available():
                  img_val = img_val.cuda()
                else:
                  img_val = img_val.to(device)

                x_rec_val, mu_val, logvar_val = model(img_val)
                MSE_val, KLD_val = vae_loss(x_rec_val, img_val,
mu_val, logvar_val)
                elbo_val = KLD_val + MSE_val
```

```
                val_loss.append((float(elbo_val)/len(img_val)))
                if batch_idx % 100 == 0:
                  print(f'VALIDATION     Batch {batch_idx} ---- loss
average {(float(elbo_val)/len(img_val))}')
                model.train()

            # Since the dataset is large, train on 'dataset_size'
samples.
            if dataset_size//batch_size == batch_idx:
              torch.save(model.state_dict(),
'/content/gdrive/MyDrive/Colab
Notebooks/assignment4/models/model_E_{}_I_{}.pth'.format(epoch,batch_i
dx))
              with open('//content/gdrive/MyDrive/Colab
Notebooks/assignment4/models/train_loss.txt', 'a') as f:
                f.write('\n')
                f.write('\n'.join(str(x) for x in train_loss[-1-
batch_idx//10:]))
                f.close()

              with open('/content/gdrive/MyDrive/Colab
Notebooks/assignment4/models/val_loss.txt', 'a') as f:
                f.write('\n')
                f.write('\n'.join(str(x) for x in val_loss[-1-
batch_idx//10:]))
                f.close()
                break

    return model, iters, train_loss, val_loss
```

Part (b) -- 4%

We first train with dimension of latent space $L=3$

We recommend to use *weight_init()* function, which helps stabilize the training process.

```
latent1 = 3
if torch.cuda.is_available():
    model_1 =
VAE(enc_in_chnl,enc_num_hidden,dec_in_chnl,dec_num_hidden,latent1,
width = width, height = height).cuda()
    model_1.weight_init(mean=0, std=0.02)
else:
    model_1 =
VAE(enc_in_chnl,enc_num_hidden,dec_in_chnl,dec_num_hidden,latent1,
width = width, height = height)
    model_1.weight_init(mean=0, std=0.02)
```

Train your model, plot the train and the validation loss graphs. Explain what is seen.

```
# Your Code Goes Here
model_1 , iters, train_loss, val_loss =
train(num_epochs,batch_size,dataset_size,model_1)
```

```
Epoch 0
TRAIN           Batch 0 ---- loss average 235.76541015625
VALIDATION      Batch 0 ---- loss average 216.5170703125
TRAIN           Batch 100 ---- loss average 105.026455078125
VALIDATION      Batch 100 ---- loss average 101.12509765625
TRAIN           Batch 200 ---- loss average 104.428798828125
VALIDATION      Batch 200 ---- loss average 93.9630859375
TRAIN           Batch 300 ---- loss average 94.199892578125
VALIDATION      Batch 300 ---- loss average 102.8199609375
TRAIN           Batch 400 ---- loss average 104.0572265625
VALIDATION      Batch 400 ---- loss average 111.78955078125
TRAIN           Batch 500 ---- loss average 103.21166015625
VALIDATION      Batch 500 ---- loss average 104.890107421875
TRAIN           Batch 600 ---- loss average 103.645927734375
VALIDATION      Batch 600 ---- loss average 100.30634765625
Epoch 1
TRAIN           Batch 0 ---- loss average 102.04869140625
VALIDATION      Batch 0 ---- loss average 106.975107421875
TRAIN           Batch 100 ---- loss average 104.723837890625
VALIDATION      Batch 100 ---- loss average 99.383349609375
TRAIN           Batch 200 ---- loss average 93.643935546875
VALIDATION      Batch 200 ---- loss average 97.0326953125
TRAIN           Batch 300 ---- loss average 102.781015625
VALIDATION      Batch 300 ---- loss average 94.114833984375
TRAIN           Batch 400 ---- loss average 91.242255859375
VALIDATION      Batch 400 ---- loss average 96.199111328125
TRAIN           Batch 500 ---- loss average 96.411259765625
VALIDATION      Batch 500 ---- loss average 94.32064453125
TRAIN           Batch 600 ---- loss average 116.374462890625
VALIDATION      Batch 600 ---- loss average 93.909873046875
Epoch 2
TRAIN           Batch 0 ---- loss average 92.835625
VALIDATION      Batch 0 ---- loss average 91.948779296875
TRAIN           Batch 100 ---- loss average 92.08939453125
VALIDATION      Batch 100 ---- loss average 104.9307421875
TRAIN           Batch 200 ---- loss average 100.661181640625
VALIDATION      Batch 200 ---- loss average 106.828291015625
TRAIN           Batch 300 ---- loss average 100.474267578125
VALIDATION      Batch 300 ---- loss average 99.85197265625
TRAIN           Batch 400 ---- loss average 99.062939453125
VALIDATION      Batch 400 ---- loss average 99.66650390625
TRAIN           Batch 500 ---- loss average 103.176015625
VALIDATION      Batch 500 ---- loss average 97.043134765625
TRAIN           Batch 600 ---- loss average 96.08517578125
VALIDATION      Batch 600 ---- loss average 100.57994140625
Epoch 3
```

```
TRAIN          Batch 0 ---- loss average 105.573203125
VALIDATION     Batch 0 ---- loss average 107.699775390625
TRAIN          Batch 100 ---- loss average 107.32552734375
VALIDATION     Batch 100 ---- loss average 88.215546875
TRAIN          Batch 200 ---- loss average 95.52150390625
VALIDATION     Batch 200 ---- loss average 106.379931640625
TRAIN          Batch 300 ---- loss average 88.747099609375
VALIDATION     Batch 300 ---- loss average 90.36763671875
TRAIN          Batch 400 ---- loss average 95.42640625
VALIDATION     Batch 400 ---- loss average 94.3798046875
TRAIN          Batch 500 ---- loss average 104.188310546875
VALIDATION     Batch 500 ---- loss average 99.58009765625
TRAIN          Batch 600 ---- loss average 101.05109375
VALIDATION     Batch 600 ---- loss average 94.280615234375
Epoch 4
TRAIN          Batch 0 ---- loss average 96.30677734375
VALIDATION     Batch 0 ---- loss average 93.430244140625
TRAIN          Batch 100 ---- loss average 87.877666015625
VALIDATION     Batch 100 ---- loss average 103.283701171875
TRAIN          Batch 200 ---- loss average 99.8544921875
VALIDATION     Batch 200 ---- loss average 100.586630859375
TRAIN          Batch 300 ---- loss average 97.416884765625
VALIDATION     Batch 300 ---- loss average 96.867314453125
TRAIN          Batch 400 ---- loss average 100.389560546875
VALIDATION     Batch 400 ---- loss average 92.89162109375
TRAIN          Batch 500 ---- loss average 95.07083984375
VALIDATION     Batch 500 ---- loss average 99.47052734375
TRAIN          Batch 600 ---- loss average 113.82166015625
VALIDATION     Batch 600 ---- loss average 104.792900390625
Epoch 5
TRAIN          Batch 0 ---- loss average 100.843701171875
VALIDATION     Batch 0 ---- loss average 108.024482421875
TRAIN          Batch 100 ---- loss average 98.439833984375
VALIDATION     Batch 100 ---- loss average 95.22435546875
TRAIN          Batch 200 ---- loss average 94.817783203125
VALIDATION     Batch 200 ---- loss average 95.64521484375
TRAIN          Batch 300 ---- loss average 99.577265625
VALIDATION     Batch 300 ---- loss average 94.59771484375
TRAIN          Batch 400 ---- loss average 104.56541015625
VALIDATION     Batch 400 ---- loss average 99.1764453125
TRAIN          Batch 500 ---- loss average 106.8534765625
VALIDATION     Batch 500 ---- loss average 97.665341796875
TRAIN          Batch 600 ---- loss average 103.63349609375
VALIDATION     Batch 600 ---- loss average 98.721533203125
Epoch 6
TRAIN          Batch 0 ---- loss average 101.4250390625
VALIDATION     Batch 0 ---- loss average 102.57431640625
TRAIN          Batch 100 ---- loss average 100.062568359375
VALIDATION     Batch 100 ---- loss average 107.72708984375
TRAIN          Batch 200 ---- loss average 108.533017578125
```

```
VALIDATION     Batch 200 ---- loss average 99.9186328125
TRAIN          Batch 300 ---- loss average 98.929228515625
VALIDATION     Batch 300 ---- loss average 97.319404296875
TRAIN          Batch 400 ---- loss average 90.48115234375
VALIDATION     Batch 400 ---- loss average 93.015576171875
TRAIN          Batch 500 ---- loss average 107.9469921875
VALIDATION     Batch 500 ---- loss average 94.48212890625
TRAIN          Batch 600 ---- loss average 97.74064453125
VALIDATION     Batch 600 ---- loss average 101.237958984375
Epoch 7
TRAIN          Batch 0 ---- loss average 108.449365234375
VALIDATION     Batch 0 ---- loss average 101.20970703125
TRAIN          Batch 100 ---- loss average 98.453212890625
VALIDATION     Batch 100 ---- loss average 90.982470703125
TRAIN          Batch 200 ---- loss average 98.258076171875
VALIDATION     Batch 200 ---- loss average 95.69728515625
TRAIN          Batch 300 ---- loss average 104.326865234375
VALIDATION     Batch 300 ---- loss average 97.969619140625
TRAIN          Batch 400 ---- loss average 101.361181640625
VALIDATION     Batch 400 ---- loss average 88.148720703125
TRAIN          Batch 500 ---- loss average 93.755234375
VALIDATION     Batch 500 ---- loss average 102.68234375
TRAIN          Batch 600 ---- loss average 94.66181640625
VALIDATION     Batch 600 ---- loss average 103.606455078125
Epoch 8
TRAIN          Batch 0 ---- loss average 88.204619140625
VALIDATION     Batch 0 ---- loss average 111.327314453125
TRAIN          Batch 100 ---- loss average 103.191318359375
VALIDATION     Batch 100 ---- loss average 94.29072265625
TRAIN          Batch 200 ---- loss average 90.842431640625
VALIDATION     Batch 200 ---- loss average 92.292138671875
TRAIN          Batch 300 ---- loss average 93.220947265625
VALIDATION     Batch 300 ---- loss average 93.92466796875
TRAIN          Batch 400 ---- loss average 116.7063671875
VALIDATION     Batch 400 ---- loss average 91.84396484375
TRAIN          Batch 500 ---- loss average 93.5301171875
VALIDATION     Batch 500 ---- loss average 86.13111328125
TRAIN          Batch 600 ---- loss average 95.138037109375
VALIDATION     Batch 600 ---- loss average 100.25283203125
Epoch 9
TRAIN          Batch 0 ---- loss average 107.879296875
VALIDATION     Batch 0 ---- loss average 103.45494140625
TRAIN          Batch 100 ---- loss average 88.41326171875
VALIDATION     Batch 100 ---- loss average 102.305439453125
TRAIN          Batch 200 ---- loss average 110.151357421875
VALIDATION     Batch 200 ---- loss average 85.24982421875
TRAIN          Batch 300 ---- loss average 96.75423828125
VALIDATION     Batch 300 ---- loss average 88.579833984375
TRAIN          Batch 400 ---- loss average 100.339853515625
VALIDATION     Batch 400 ---- loss average 99.295927734375
```

```
TRAIN          Batch 500 ---- loss average 110.811220703125
VALIDATION     Batch 500 ---- loss average 103.385595703125
TRAIN          Batch 600 ---- loss average 97.60923828125
VALIDATION     Batch 600 ---- loss average 89.83142578125
Epoch 10
TRAIN          Batch 0 ---- loss average 105.590703125
VALIDATION     Batch 0 ---- loss average 87.565927734375
TRAIN          Batch 100 ---- loss average 96.66451171875
VALIDATION     Batch 100 ---- loss average 95.67513671875
TRAIN          Batch 200 ---- loss average 91.3084375
VALIDATION     Batch 200 ---- loss average 111.700234375
TRAIN          Batch 300 ---- loss average 91.979150390625
VALIDATION     Batch 300 ---- loss average 93.060947265625
TRAIN          Batch 400 ---- loss average 102.01580078125
VALIDATION     Batch 400 ---- loss average 94.784384765625
TRAIN          Batch 500 ---- loss average 101.1606640625
VALIDATION     Batch 500 ---- loss average 101.255302734375
TRAIN          Batch 600 ---- loss average 84.47712890625
VALIDATION     Batch 600 ---- loss average 113.592724609375
Epoch 11
TRAIN          Batch 0 ---- loss average 96.9640234375
VALIDATION     Batch 0 ---- loss average 94.937333984375
TRAIN          Batch 100 ---- loss average 96.480615234375
VALIDATION     Batch 100 ---- loss average 99.397353515625
TRAIN          Batch 200 ---- loss average 89.63330078125
VALIDATION     Batch 200 ---- loss average 89.009951171875
TRAIN          Batch 300 ---- loss average 99.424296875
VALIDATION     Batch 300 ---- loss average 89.810234375
TRAIN          Batch 400 ---- loss average 99.38251953125
VALIDATION     Batch 400 ---- loss average 99.99208984375
TRAIN          Batch 500 ---- loss average 95.250166015625
VALIDATION     Batch 500 ---- loss average 97.719326171875
TRAIN          Batch 600 ---- loss average 100.21498046875
VALIDATION     Batch 600 ---- loss average 93.52775390625
Epoch 12
TRAIN          Batch 0 ---- loss average 104.98669921875
VALIDATION     Batch 0 ---- loss average 91.840556640625
TRAIN          Batch 100 ---- loss average 95.95126953125
VALIDATION     Batch 100 ---- loss average 84.729736328125
TRAIN          Batch 200 ---- loss average 89.49603515625
VALIDATION     Batch 200 ---- loss average 99.1266796875
TRAIN          Batch 300 ---- loss average 93.49443359375
VALIDATION     Batch 300 ---- loss average 90.999599609375
TRAIN          Batch 400 ---- loss average 94.050859375
VALIDATION     Batch 400 ---- loss average 94.145439453125
TRAIN          Batch 500 ---- loss average 96.76681640625
VALIDATION     Batch 500 ---- loss average 84.80140625
TRAIN          Batch 600 ---- loss average 94.95408203125
VALIDATION     Batch 600 ---- loss average 100.6780078125
Epoch 13
```

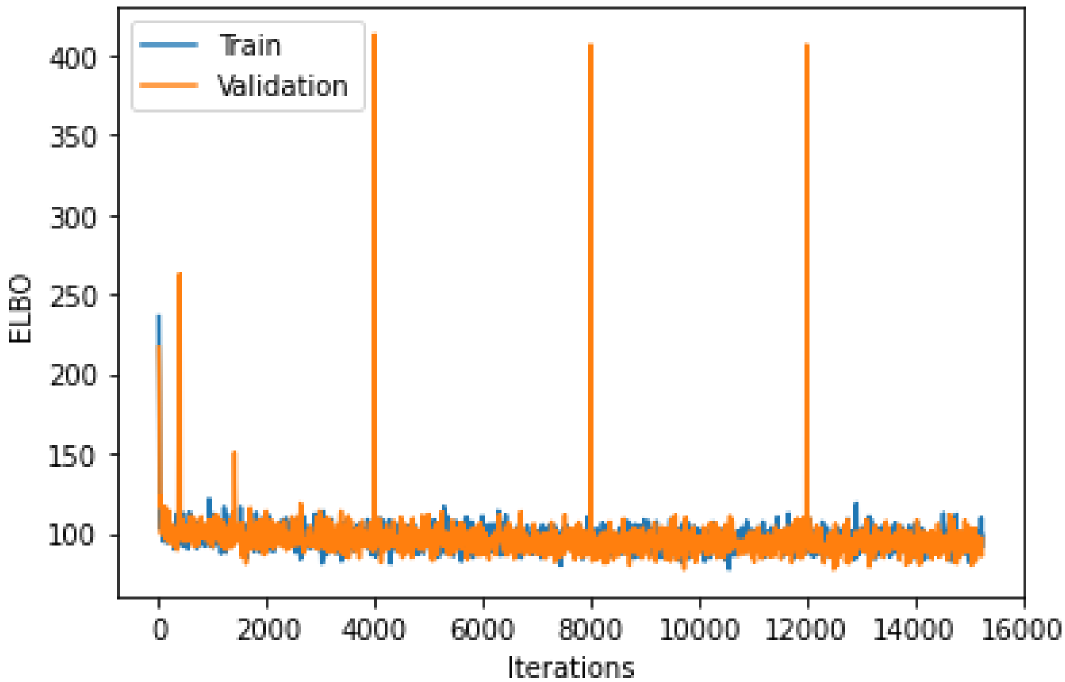
```
TRAIN          Batch 0 ---- loss average 98.843828125
VALIDATION     Batch 0 ---- loss average 94.05873046875
TRAIN          Batch 100 ---- loss average 91.19779296875
VALIDATION     Batch 100 ---- loss average 93.370556640625
TRAIN          Batch 200 ---- loss average 99.25369140625
VALIDATION     Batch 200 ---- loss average 84.333310546875
TRAIN          Batch 300 ---- loss average 93.011669921875
VALIDATION     Batch 300 ---- loss average 84.79275390625
TRAIN          Batch 400 ---- loss average 96.34830078125
VALIDATION     Batch 400 ---- loss average 102.8155859375
TRAIN          Batch 500 ---- loss average 95.192470703125
VALIDATION     Batch 500 ---- loss average 100.73015625
TRAIN          Batch 600 ---- loss average 103.486259765625
VALIDATION     Batch 600 ---- loss average 89.7561328125
Epoch 14
TRAIN          Batch 0 ---- loss average 93.5393359375
VALIDATION     Batch 0 ---- loss average 93.481298828125
TRAIN          Batch 100 ---- loss average 107.641572265625
VALIDATION     Batch 100 ---- loss average 96.687939453125
TRAIN          Batch 200 ---- loss average 99.0170703125
VALIDATION     Batch 200 ---- loss average 89.250390625
TRAIN          Batch 300 ---- loss average 91.389111328125
VALIDATION     Batch 300 ---- loss average 98.487255859375
TRAIN          Batch 400 ---- loss average 97.46650390625
VALIDATION     Batch 400 ---- loss average 84.189365234375
TRAIN          Batch 500 ---- loss average 95.100146484375
VALIDATION     Batch 500 ---- loss average 92.454091796875
TRAIN          Batch 600 ---- loss average 90.369853515625
VALIDATION     Batch 600 ---- loss average 95.574189453125
Epoch 15
TRAIN          Batch 0 ---- loss average 92.275556640625
VALIDATION     Batch 0 ---- loss average 95.039873046875
TRAIN          Batch 100 ---- loss average 100.113701171875
VALIDATION     Batch 100 ---- loss average 98.465205078125
TRAIN          Batch 200 ---- loss average 95.774638671875
VALIDATION     Batch 200 ---- loss average 97.332001953125
TRAIN          Batch 300 ---- loss average 95.488232421875
VALIDATION     Batch 300 ---- loss average 86.084228515625
TRAIN          Batch 400 ---- loss average 87.896064453125
VALIDATION     Batch 400 ---- loss average 87.3480859375
TRAIN          Batch 500 ---- loss average 82.587646484375
VALIDATION     Batch 500 ---- loss average 86.279794921875
TRAIN          Batch 600 ---- loss average 87.681796875
VALIDATION     Batch 600 ---- loss average 110.004931640625
Epoch 16
TRAIN          Batch 0 ---- loss average 93.955185546875
VALIDATION     Batch 0 ---- loss average 91.342783203125
TRAIN          Batch 100 ---- loss average 90.609033203125
VALIDATION     Batch 100 ---- loss average 85.431572265625
TRAIN          Batch 200 ---- loss average 103.1344921875
```

```
VALIDATION     Batch 200 ---- loss average 87.505126953125
TRAIN          Batch 300 ---- loss average 94.549013671875
VALIDATION     Batch 300 ---- loss average 93.12431640625
TRAIN          Batch 400 ---- loss average 93.646923828125
VALIDATION     Batch 400 ---- loss average 97.583759765625
TRAIN          Batch 500 ---- loss average 93.820029296875
VALIDATION     Batch 500 ---- loss average 91.466025390625
TRAIN          Batch 600 ---- loss average 89.766865234375
VALIDATION     Batch 600 ---- loss average 101.102109375
Epoch 17
TRAIN          Batch 0 ---- loss average 88.85701171875
VALIDATION     Batch 0 ---- loss average 103.48974609375
TRAIN          Batch 100 ---- loss average 98.755595703125
VALIDATION     Batch 100 ---- loss average 101.800927734375
TRAIN          Batch 200 ---- loss average 91.0058984375
VALIDATION     Batch 200 ---- loss average 110.813603515625
TRAIN          Batch 300 ---- loss average 92.9874609375
VALIDATION     Batch 300 ---- loss average 94.004453125
TRAIN          Batch 400 ---- loss average 89.535498046875
VALIDATION     Batch 400 ---- loss average 93.68330078125
TRAIN          Batch 500 ---- loss average 87.966826171875
VALIDATION     Batch 500 ---- loss average 96.793232421875
TRAIN          Batch 600 ---- loss average 93.2644921875
VALIDATION     Batch 600 ---- loss average 85.72849609375
Epoch 18
TRAIN          Batch 0 ---- loss average 102.74892578125
VALIDATION     Batch 0 ---- loss average 100.8171484375
TRAIN          Batch 100 ---- loss average 97.587421875
VALIDATION     Batch 100 ---- loss average 96.5491796875
TRAIN          Batch 200 ---- loss average 107.086279296875
VALIDATION     Batch 200 ---- loss average 95.760546875
TRAIN          Batch 300 ---- loss average 101.208759765625
VALIDATION     Batch 300 ---- loss average 99.76205078125
TRAIN          Batch 400 ---- loss average 92.99224609375
VALIDATION     Batch 400 ---- loss average 97.49974609375
TRAIN          Batch 500 ---- loss average 99.30578125
VALIDATION     Batch 500 ---- loss average 97.693876953125
TRAIN          Batch 600 ---- loss average 88.120673828125
VALIDATION     Batch 600 ---- loss average 91.08771484375
Epoch 19
TRAIN          Batch 0 ---- loss average 101.38546875
VALIDATION     Batch 0 ---- loss average 101.99634765625
TRAIN          Batch 100 ---- loss average 95.815537109375
VALIDATION     Batch 100 ---- loss average 99.130400390625
TRAIN          Batch 200 ---- loss average 91.125185546875
VALIDATION     Batch 200 ---- loss average 102.120166015625
TRAIN          Batch 300 ---- loss average 94.98755859375
VALIDATION     Batch 300 ---- loss average 84.0226171875
TRAIN          Batch 400 ---- loss average 87.15806640625
VALIDATION     Batch 400 ---- loss average 406.2910563151042
```

```
TRAIN          Batch 500 ---- loss average 90.34689453125
VALIDATION     Batch 500 ---- loss average 90.83787109375
TRAIN          Batch 600 ---- loss average 100.071298828125
VALIDATION     Batch 600 ---- loss average 90.711572265625
Epoch 20
TRAIN          Batch 0 ---- loss average 89.270673828125
VALIDATION     Batch 0 ---- loss average 89.23349609375
TRAIN          Batch 100 ---- loss average 83.08630859375
VALIDATION     Batch 100 ---- loss average 90.559208984375
TRAIN          Batch 200 ---- loss average 93.079228515625
VALIDATION     Batch 200 ---- loss average 87.66087890625
TRAIN          Batch 300 ---- loss average 90.09900390625
VALIDATION     Batch 300 ---- loss average 94.05337890625
TRAIN          Batch 400 ---- loss average 94.055146484375
VALIDATION     Batch 400 ---- loss average 85.3195703125
TRAIN          Batch 500 ---- loss average 97.627822265625
VALIDATION     Batch 500 ---- loss average 105.3951953125
TRAIN          Batch 600 ---- loss average 101.77673828125
VALIDATION     Batch 600 ---- loss average 92.503779296875
Epoch 21
TRAIN          Batch 0 ---- loss average 91.594599609375
VALIDATION     Batch 0 ---- loss average 84.046318359375
TRAIN          Batch 100 ---- loss average 118.776904296875
VALIDATION     Batch 100 ---- loss average 91.80552734375
TRAIN          Batch 200 ---- loss average 94.5155078125
VALIDATION     Batch 200 ---- loss average 97.41564453125
TRAIN          Batch 300 ---- loss average 88.673935546875
VALIDATION     Batch 300 ---- loss average 97.04919921875
TRAIN          Batch 400 ---- loss average 97.906865234375
VALIDATION     Batch 400 ---- loss average 94.2945703125
TRAIN          Batch 500 ---- loss average 86.042373046875
VALIDATION     Batch 500 ---- loss average 96.06484375
TRAIN          Batch 600 ---- loss average 90.669091796875
VALIDATION     Batch 600 ---- loss average 84.787978515625
Epoch 22
TRAIN          Batch 0 ---- loss average 92.622099609375
VALIDATION     Batch 0 ---- loss average 101.634150390625
TRAIN          Batch 100 ---- loss average 86.27923828125
VALIDATION     Batch 100 ---- loss average 97.344951171875
TRAIN          Batch 200 ---- loss average 99.474052734375
VALIDATION     Batch 200 ---- loss average 90.8286328125
TRAIN          Batch 300 ---- loss average 92.85876953125
VALIDATION     Batch 300 ---- loss average 98.749521484375
TRAIN          Batch 400 ---- loss average 93.461005859375
VALIDATION     Batch 400 ---- loss average 90.438623046875
TRAIN          Batch 500 ---- loss average 82.81361328125
VALIDATION     Batch 500 ---- loss average 97.666689453125
TRAIN          Batch 600 ---- loss average 103.793134765625
VALIDATION     Batch 600 ---- loss average 106.378251953125
Epoch 23
```

```
TRAIN          Batch 0 ---- loss average 107.349912109375
VALIDATION     Batch 0 ---- loss average 108.32673828125
TRAIN          Batch 100 ---- loss average 103.24947265625
VALIDATION     Batch 100 ---- loss average 92.656416015625
TRAIN          Batch 200 ---- loss average 92.290009765625
VALIDATION     Batch 200 ---- loss average 100.081376953125
TRAIN          Batch 300 ---- loss average 97.28466796875
VALIDATION     Batch 300 ---- loss average 87.989248046875
TRAIN          Batch 400 ---- loss average 92.688671875
VALIDATION     Batch 400 ---- loss average 89.001796875
TRAIN          Batch 500 ---- loss average 93.580263671875
VALIDATION     Batch 500 ---- loss average 94.09423828125
TRAIN          Batch 600 ---- loss average 106.638037109375
VALIDATION     Batch 600 ---- loss average 96.20712890625
Epoch 24
TRAIN          Batch 0 ---- loss average 95.232646484375
VALIDATION     Batch 0 ---- loss average 111.855947265625
TRAIN          Batch 100 ---- loss average 95.012470703125
VALIDATION     Batch 100 ---- loss average 90.004228515625
TRAIN          Batch 200 ---- loss average 98.42455078125
VALIDATION     Batch 200 ---- loss average 86.3102734375
TRAIN          Batch 300 ---- loss average 90.219189453125
VALIDATION     Batch 300 ---- loss average 88.042041015625
TRAIN          Batch 400 ---- loss average 92.53603515625
VALIDATION     Batch 400 ---- loss average 79.8242041015625
TRAIN          Batch 500 ---- loss average 93.00658203125
VALIDATION     Batch 500 ---- loss average 98.07486328125
TRAIN          Batch 600 ---- loss average 98.8559765625
VALIDATION     Batch 600 ---- loss average 96.48203125
```

```python
def plot_loss(iters, train_loss, val_loss):
  iters = [10*x for x in range(len(train_loss))]
  plt.plot(iters, train_loss, label='Train')
  plt.plot(iters, val_loss, label='Validation')
  plt.xlabel('Iterations')
  plt.ylabel('ELBO')
  plt.legend()
  plt.show()

plot_loss(iters, train_loss, val_loss)
```



Our Answer

First, we can see both test and validation losses drop dramatically over the first few iterations.

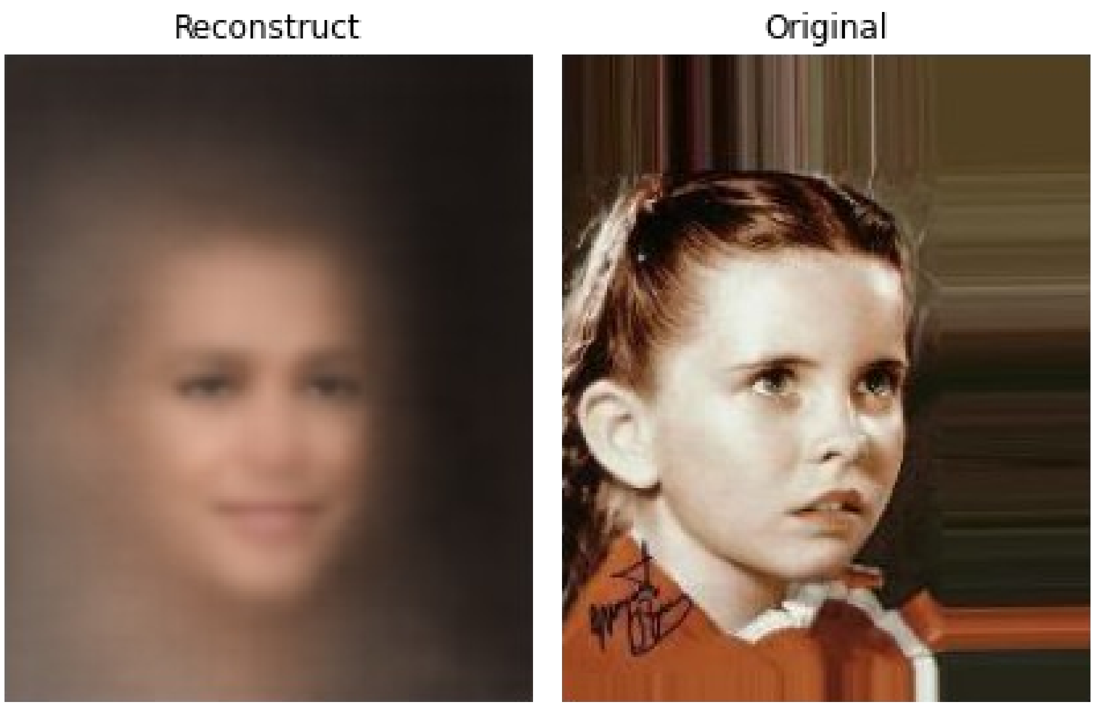
From that moment on, for the most part the two graphs are similar in having ELBO loss of roughly 100 with a stochastic change around that number.

We must adress the spikes we see in the validation graph. These are an inevitable result of Mini-Batch Gradient Descent in Adam. Some mini-batches have unlucky data for the optimization, inducing those spikes we see in our cost function.

Visualize, from the test dataset, an original image against a reconstructed image. Has the model reconstructed the image successfully? Explain.

```
# Your Code Goes Here

def plot_reconstructed(model,test_loader):
      model.eval()
      for i,image in enumerate(test_loader):
        images,_ = image
        if torch.cuda.is_available():
          images = images.cuda()
        else:
          images = images.to(device)
        #reconstruct
        x_rec=model(images)
        fig, axes =plt.subplots(1,2)
        #plot
```

```
        axes[0].imshow(x_rec[0].cpu().detach().numpy()
[10].transpose(1,2,0))
        axes[0].set_title("Reconstruct")
        axes[0].axis('off')
        axes[1].imshow(images.cpu().detach().numpy()
[10].transpose(1,2,0))
        axes[1].set_title("Original")
        axes[1].axis('off')
        plt.tight_layout()
        plt.show()
        break
      return

plot_reconstructed(model_1,test_loader)
```



Our Answer

We have managed to reconstruct a human face. However, we see that the image has very few details and looks like a general face floating in space. The facial features are not similar to the original image, nor are the background or posture of the person.

We believe the lack of features is mostly due to our low dimension latent space and small number of epochs. Unfortunately, due to low computational power we couldn't change that much further and will only go up to latent space of 10 dimensions and maintain a small number of epochs.

Part (c) -- 7%

Next, we train with larger L>3

Based on the results for $L=3$, choose a larger L to improve your results. Train new model with your choice for L.

```
latent2 = 10 # TO DO: Choose latent space dimension.
num_epochs = 15  # smaller num of epochs to allow computation with 
decent time

if torch.cuda.is_available():
    model_2 = 
VAE(enc_in_chnl,enc_num_hidden,dec_in_chnl,dec_num_hidden,latent2, 
width = width, height = height).cuda()
    model_2.weight_init(mean=0, std=0.02)
else:
    model_2 = 
VAE(enc_in_chnl,enc_num_hidden,dec_in_chnl,dec_num_hidden,latent2, 
width = width, height = height)
    model_2.weight_init(mean=0, std=0.02)
```

Plot the train and the validation loss graphs. Explain what is seen.

```
# Your Code Goes Here
torch.cuda.empty_cache()
model_2 , iters_2, train_loss_2, val_loss_2 = 
train(num_epochs,batch_size,dataset_size,model_2)
```

```
Epoch 0
TRAIN          Batch 0 ---- loss average 226.8038671875
VALIDATION     Batch 0 ---- loss average 207.8993359375
TRAIN          Batch 100 ---- loss average 76.3603076171875
VALIDATION     Batch 100 ---- loss average 76.3194775390625
TRAIN          Batch 200 ---- loss average 74.04162109375
VALIDATION     Batch 200 ---- loss average 74.1803271484375
TRAIN          Batch 300 ---- loss average 77.808408203125
VALIDATION     Batch 300 ---- loss average 71.0316943359375
TRAIN          Batch 400 ---- loss average 68.372431640625
VALIDATION     Batch 400 ---- loss average 73.812109375
TRAIN          Batch 500 ---- loss average 65.671796875
VALIDATION     Batch 500 ---- loss average 71.8195703125
TRAIN          Batch 600 ---- loss average 71.1601220703125
VALIDATION     Batch 600 ---- loss average 58.1686572265625
Epoch 1
TRAIN          Batch 0 ---- loss average 66.2667431640625
VALIDATION     Batch 0 ---- loss average 70.757890625
TRAIN          Batch 100 ---- loss average 62.096123046875
VALIDATION     Batch 100 ---- loss average 62.6597802734375
TRAIN          Batch 200 ---- loss average 63.5126708984375
VALIDATION     Batch 200 ---- loss average 64.53833984375
TRAIN          Batch 300 ---- loss average 63.35068359375
VALIDATION     Batch 300 ---- loss average 71.110908203125
TRAIN          Batch 400 ---- loss average 65.2507177734375
VALIDATION     Batch 400 ---- loss average 64.8621826171875
```

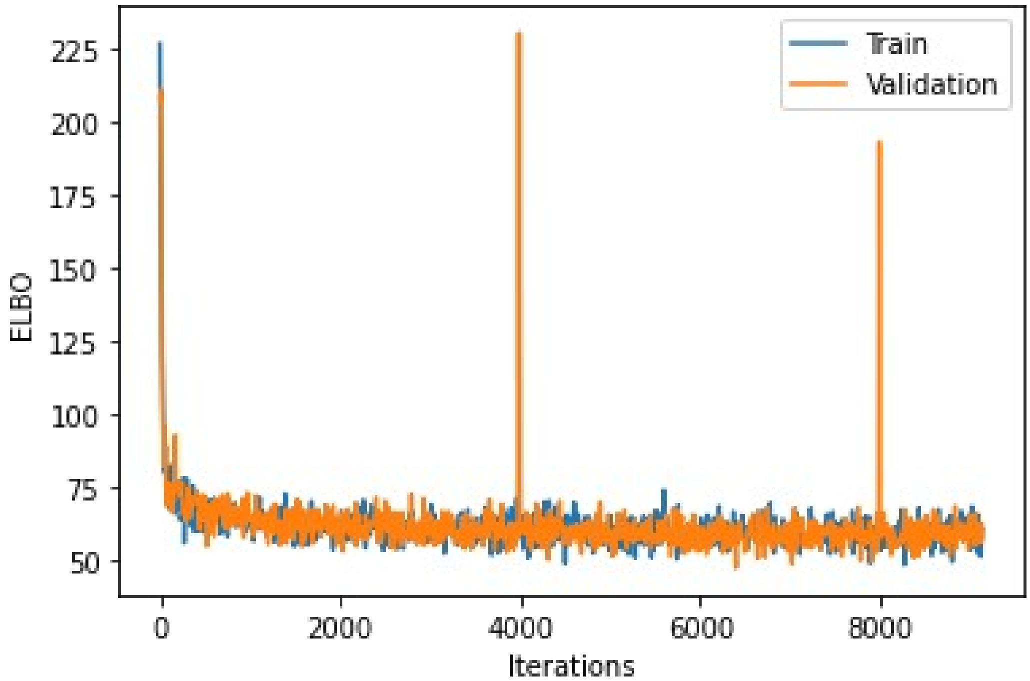
```
TRAIN           Batch 500 ---- loss average 71.316982421875
VALIDATION      Batch 500 ---- loss average 66.3798388671875
TRAIN           Batch 600 ---- loss average 60.48462890625
VALIDATION      Batch 600 ---- loss average 59.9750830078125
Epoch 2
TRAIN           Batch 0 ---- loss average 62.674453125
VALIDATION      Batch 0 ---- loss average 66.4802685546875
TRAIN           Batch 100 ---- loss average 64.0879638671875
VALIDATION      Batch 100 ---- loss average 63.3741015625
TRAIN           Batch 200 ---- loss average 59.163916015625
VALIDATION      Batch 200 ---- loss average 67.388359375
TRAIN           Batch 300 ---- loss average 55.4208447265625
VALIDATION      Batch 300 ---- loss average 70.71896484375
TRAIN           Batch 400 ---- loss average 57.3972509765625
VALIDATION      Batch 400 ---- loss average 66.2403564453125
TRAIN           Batch 500 ---- loss average 61.607236328125
VALIDATION      Batch 500 ---- loss average 66.9146533203125
TRAIN           Batch 600 ---- loss average 60.465302734375
VALIDATION      Batch 600 ---- loss average 60.88109375
Epoch 3
TRAIN           Batch 0 ---- loss average 62.3498046875
VALIDATION      Batch 0 ---- loss average 62.7823681640625
TRAIN           Batch 100 ---- loss average 64.7112939453125
VALIDATION      Batch 100 ---- loss average 62.028125
TRAIN           Batch 200 ---- loss average 64.309287109375
VALIDATION      Batch 200 ---- loss average 52.8696142578125
TRAIN           Batch 300 ---- loss average 60.7706591796875
VALIDATION      Batch 300 ---- loss average 63.16140625
TRAIN           Batch 400 ---- loss average 60.5839501953125
VALIDATION      Batch 400 ---- loss average 60.5989208984375
TRAIN           Batch 500 ---- loss average 58.4671826171875
VALIDATION      Batch 500 ---- loss average 60.9469140625
TRAIN           Batch 600 ---- loss average 56.019345703125
VALIDATION      Batch 600 ---- loss average 66.73232421875
Epoch 4
TRAIN           Batch 0 ---- loss average 60.1792529296875
VALIDATION      Batch 0 ---- loss average 55.6224365234375
TRAIN           Batch 100 ---- loss average 67.3970263671875
VALIDATION      Batch 100 ---- loss average 59.9996875
TRAIN           Batch 200 ---- loss average 63.05140625
VALIDATION      Batch 200 ---- loss average 63.3740966796875
TRAIN           Batch 300 ---- loss average 63.185244140625
VALIDATION      Batch 300 ---- loss average 58.7326171875
TRAIN           Batch 400 ---- loss average 59.9279736328125
VALIDATION      Batch 400 ---- loss average 62.5300390625
TRAIN           Batch 500 ---- loss average 64.80267578125
VALIDATION      Batch 500 ---- loss average 55.0260302734375
TRAIN           Batch 600 ---- loss average 65.9164013671875
VALIDATION      Batch 600 ---- loss average 54.9276806640625
Epoch 5
```

```
TRAIN          Batch 0 ---- loss average 64.03595703125
VALIDATION     Batch 0 ---- loss average 59.09912109375
TRAIN          Batch 100 ---- loss average 61.3027294921875
VALIDATION     Batch 100 ---- loss average 56.5444921875
TRAIN          Batch 200 ---- loss average 63.595380859375
VALIDATION     Batch 200 ---- loss average 63.36525390625
TRAIN          Batch 300 ---- loss average 57.282998046875
VALIDATION     Batch 300 ---- loss average 58.154814453125
TRAIN          Batch 400 ---- loss average 54.7438330078125
VALIDATION     Batch 400 ---- loss average 61.925009765625
TRAIN          Batch 500 ---- loss average 59.016669921875
VALIDATION     Batch 500 ---- loss average 57.81056640625
TRAIN          Batch 600 ---- loss average 62.13583984375
VALIDATION     Batch 600 ---- loss average 57.7737060546875
Epoch 6
TRAIN          Batch 0 ---- loss average 64.938095703125
VALIDATION     Batch 0 ---- loss average 70.695966796875
TRAIN          Batch 100 ---- loss average 52.31171875
VALIDATION     Batch 100 ---- loss average 62.4657373046875
TRAIN          Batch 200 ---- loss average 57.062265625
VALIDATION     Batch 200 ---- loss average 59.98291015625
TRAIN          Batch 300 ---- loss average 70.960048828125
VALIDATION     Batch 300 ---- loss average 57.7641650390625
TRAIN          Batch 400 ---- loss average 61.8131103515625
VALIDATION     Batch 400 ---- loss average 66.544296875
TRAIN          Batch 500 ---- loss average 66.0472021484375
VALIDATION     Batch 500 ---- loss average 58.4420556640625
TRAIN          Batch 600 ---- loss average 57.323173828125
VALIDATION     Batch 600 ---- loss average 64.0026611328125
Epoch 7
TRAIN          Batch 0 ---- loss average 58.063544921875
VALIDATION     Batch 0 ---- loss average 59.2815380859375
TRAIN          Batch 100 ---- loss average 57.898935546875
VALIDATION     Batch 100 ---- loss average 56.4331005859375
TRAIN          Batch 200 ---- loss average 64.045498046875
VALIDATION     Batch 200 ---- loss average 62.0359814453125
TRAIN          Batch 300 ---- loss average 63.099794921875
VALIDATION     Batch 300 ---- loss average 61.7588916015625
TRAIN          Batch 400 ---- loss average 57.2026220703125
VALIDATION     Batch 400 ---- loss average 60.8770849609375
TRAIN          Batch 500 ---- loss average 64.7220458984375
VALIDATION     Batch 500 ---- loss average 61.897138671875
TRAIN          Batch 600 ---- loss average 59.292421875
VALIDATION     Batch 600 ---- loss average 54.693701171875
Epoch 8
TRAIN          Batch 0 ---- loss average 60.100419921875
VALIDATION     Batch 0 ---- loss average 59.914365234375
TRAIN          Batch 100 ---- loss average 58.466513671875
VALIDATION     Batch 100 ---- loss average 65.4226220703125
TRAIN          Batch 200 ---- loss average 57.9996044921875
```

```
VALIDATION     Batch 200 ---- loss average 63.684365234375
TRAIN          Batch 300 ---- loss average 63.9933154296875
VALIDATION     Batch 300 ---- loss average 53.6647021484375
TRAIN          Batch 400 ---- loss average 50.714912109375
VALIDATION     Batch 400 ---- loss average 64.1142578125
TRAIN          Batch 500 ---- loss average 54.7020556640625
VALIDATION     Batch 500 ---- loss average 58.2388916015625
TRAIN          Batch 600 ---- loss average 53.0561376953125
VALIDATION     Batch 600 ---- loss average 57.9926220703125
Epoch 9
TRAIN          Batch 0 ---- loss average 56.643564453125
VALIDATION     Batch 0 ---- loss average 58.6267529296875
TRAIN          Batch 100 ---- loss average 63.8416748046875
VALIDATION     Batch 100 ---- loss average 56.797783203125
TRAIN          Batch 200 ---- loss average 56.6380859375
VALIDATION     Batch 200 ---- loss average 59.5407275390625
TRAIN          Batch 300 ---- loss average 52.8562939453125
VALIDATION     Batch 300 ---- loss average 62.9423828125
TRAIN          Batch 400 ---- loss average 57.0414794921875
VALIDATION     Batch 400 ---- loss average 59.829326171875
TRAIN          Batch 500 ---- loss average 57.224580078125
VALIDATION     Batch 500 ---- loss average 53.6688916015625
TRAIN          Batch 600 ---- loss average 57.9363916015625
VALIDATION     Batch 600 ---- loss average 60.804443359375
Epoch 10
TRAIN          Batch 0 ---- loss average 60.0925634765625
VALIDATION     Batch 0 ---- loss average 62.600869140625
TRAIN          Batch 100 ---- loss average 59.598486328125
VALIDATION     Batch 100 ---- loss average 64.5685205078125
TRAIN          Batch 200 ---- loss average 59.669130859375
VALIDATION     Batch 200 ---- loss average 55.042109375
TRAIN          Batch 300 ---- loss average 63.166435546875
VALIDATION     Batch 300 ---- loss average 47.2216796875
TRAIN          Batch 400 ---- loss average 61.6781787109375
VALIDATION     Batch 400 ---- loss average 56.2087939453125
TRAIN          Batch 500 ---- loss average 62.5084912109375
VALIDATION     Batch 500 ---- loss average 58.1787744140625
TRAIN          Batch 600 ---- loss average 58.963193359375
VALIDATION     Batch 600 ---- loss average 55.9466357421875
Epoch 11
TRAIN          Batch 0 ---- loss average 62.908681640625
VALIDATION     Batch 0 ---- loss average 58.5231494140625
TRAIN          Batch 100 ---- loss average 57.7175244140625
VALIDATION     Batch 100 ---- loss average 61.4799267578125
TRAIN          Batch 200 ---- loss average 56.9952587890625
VALIDATION     Batch 200 ---- loss average 55.5058837890625
TRAIN          Batch 300 ---- loss average 58.5309423828125
VALIDATION     Batch 300 ---- loss average 57.8002392578125
TRAIN          Batch 400 ---- loss average 51.9378076171875
VALIDATION     Batch 400 ---- loss average 61.91650390625
```

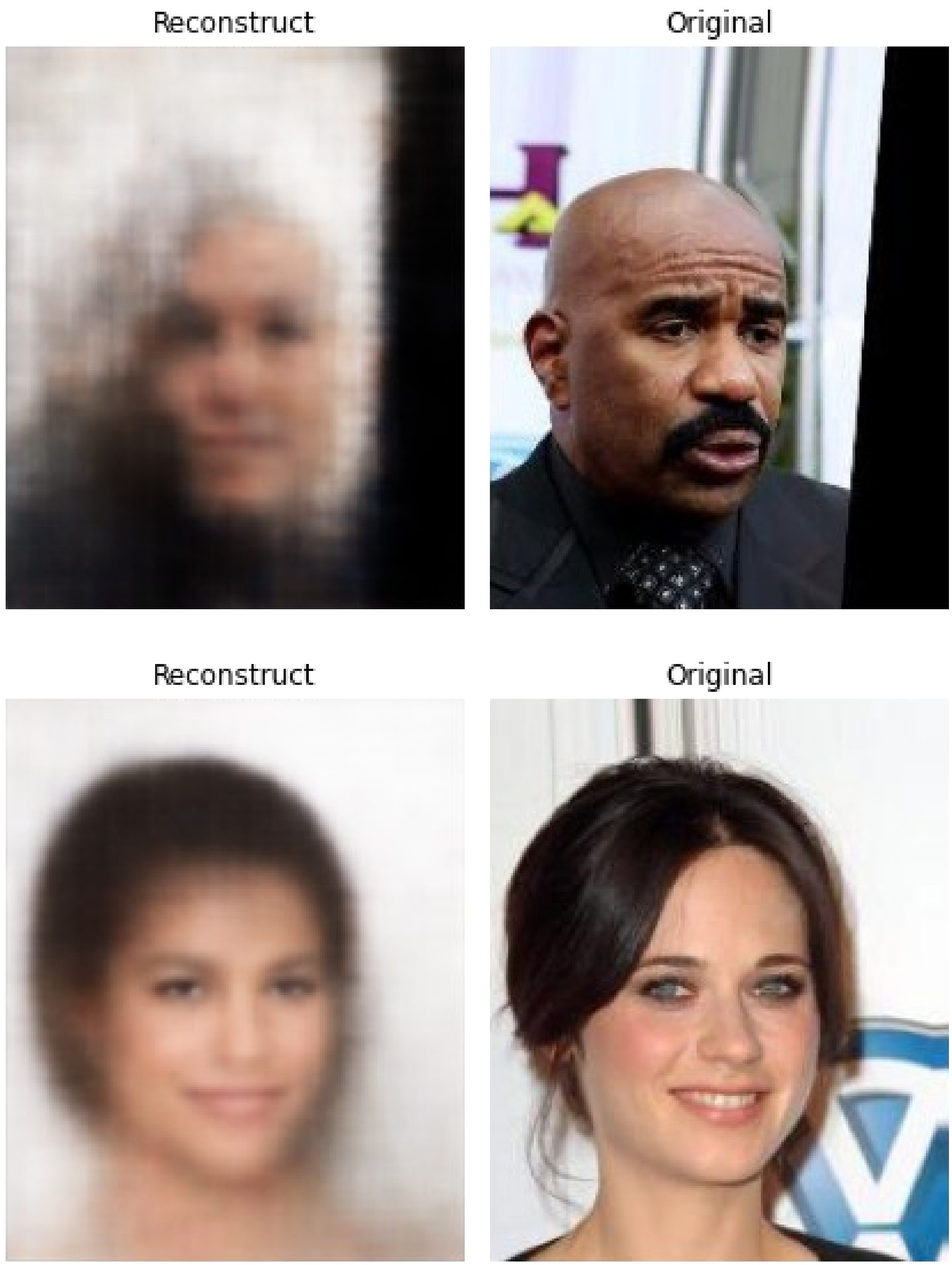
```
TRAIN          Batch 500 ---- loss average 59.971748046875
VALIDATION     Batch 500 ---- loss average 63.397265625
TRAIN          Batch 600 ---- loss average 59.9121142578125
VALIDATION     Batch 600 ---- loss average 57.295263671875
Epoch 12
TRAIN          Batch 0 ---- loss average 58.6170556640625
VALIDATION     Batch 0 ---- loss average 61.7479052734375
TRAIN          Batch 100 ---- loss average 55.528359375
VALIDATION     Batch 100 ---- loss average 62.50189453125
TRAIN          Batch 200 ---- loss average 59.9693896484375
VALIDATION     Batch 200 ---- loss average 61.3543701171875
TRAIN          Batch 300 ---- loss average 62.8419140625
VALIDATION     Batch 300 ---- loss average 62.9887158203125
TRAIN          Batch 400 ---- loss average 62.3035400390625
VALIDATION     Batch 400 ---- loss average 61.38796875
TRAIN          Batch 500 ---- loss average 59.1056689453125
VALIDATION     Batch 500 ---- loss average 57.46171875
TRAIN          Batch 600 ---- loss average 60.3559912109375
VALIDATION     Batch 600 ---- loss average 54.8812548828125
Epoch 13
TRAIN          Batch 0 ---- loss average 57.9943701171875
VALIDATION     Batch 0 ---- loss average 57.83052734375
TRAIN          Batch 100 ---- loss average 55.5617626953125
VALIDATION     Batch 100 ---- loss average 60.575
TRAIN          Batch 200 ---- loss average 56.9167333984375
VALIDATION     Batch 200 ---- loss average 61.13505859375
TRAIN          Batch 300 ---- loss average 58.493173828125
VALIDATION     Batch 300 ---- loss average 58.200966796875
TRAIN          Batch 400 ---- loss average 58.614482421875
VALIDATION     Batch 400 ---- loss average 60.9580810546875
TRAIN          Batch 500 ---- loss average 67.84888671875
VALIDATION     Batch 500 ---- loss average 58.603037109375
TRAIN          Batch 600 ---- loss average 56.0293505859375
VALIDATION     Batch 600 ---- loss average 60.87802734375
Epoch 14
TRAIN          Batch 0 ---- loss average 54.7479296875
VALIDATION     Batch 0 ---- loss average 61.881171875
TRAIN          Batch 100 ---- loss average 58.8690185546875
VALIDATION     Batch 100 ---- loss average 60.007041015625
TRAIN          Batch 200 ---- loss average 54.32640625
VALIDATION     Batch 200 ---- loss average 54.5539990234375
TRAIN          Batch 300 ---- loss average 63.976953125
VALIDATION     Batch 300 ---- loss average 53.76580078125
TRAIN          Batch 400 ---- loss average 63.898193359375
VALIDATION     Batch 400 ---- loss average 60.969697265625
TRAIN          Batch 500 ---- loss average 54.38828125
VALIDATION     Batch 500 ---- loss average 60.1455908203125
TRAIN          Batch 600 ---- loss average 60.345126953125
VALIDATION     Batch 600 ---- loss average 57.525791015625
```

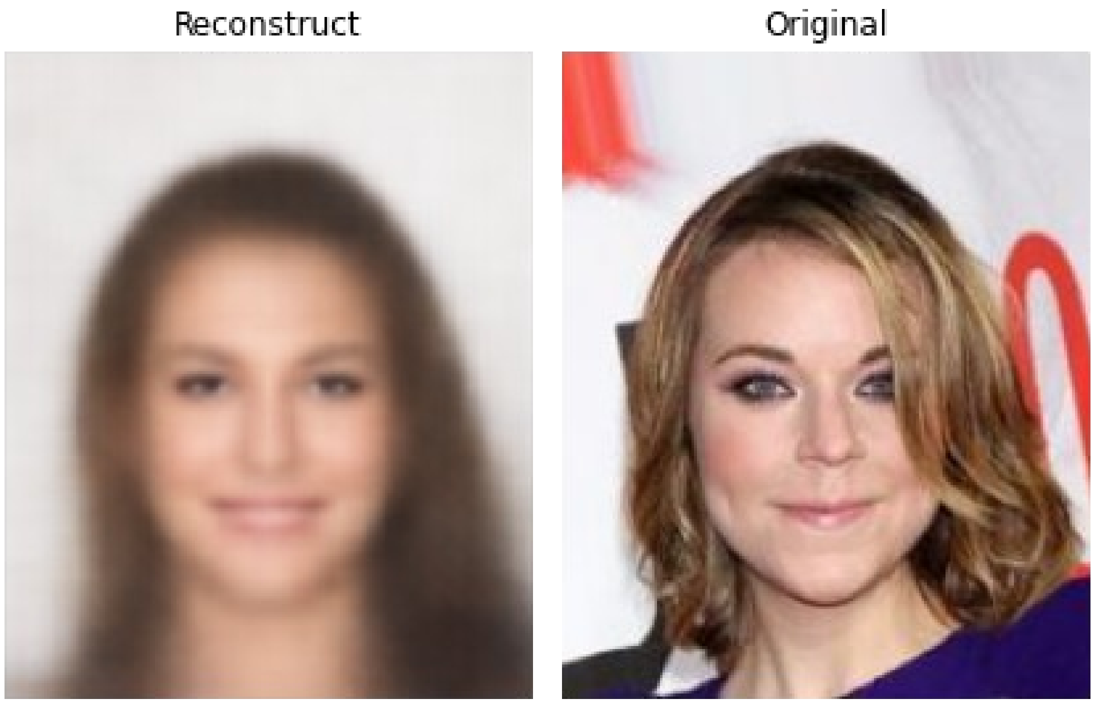
```
plot_loss(iters_2, train_loss_2, val_loss_2)
```



Visualize, from the test dataset, an original image against a reconstructed image. Has the model reconstructed the image successfully? Are the images identical? Explain.

```
# Your Code Goes Here
plot_reconstructed(model_2,test_loader)
plot_reconstructed(model_2,test_loader)
plot_reconstructed(model_2,test_loader)
```


Reconstruct
Original
Reconstruct
Original



Our Answer

When we increase the dimension of the latent space we immediately see an increase in reconstruction details. The angles, hair style, background and skin tone were reconstructed much better with this model than the previous one.

Still this result is imperfect and much better reconstruction can be achieved with higher-dimension latent space or with using a GAN model.

What will happened if we choose extremely high dimension for the latent space?

Our Answer

We can try using higher dimension for the latent space, and at the expense of computation time get better detail in our images.

However, if we chose an extremely high dimension we may face the high-dimensional small-sample-size (HDSSS) problem as published 10.1142/S1469026820500029.

This is because a high-dimensional latent space allows for a large number of possible configurations, which can make it difficult for the model to accurately capture the underlying structure of the data. The model would therefore be prone to overfitting.

Did you output blurry reconstructed images? If the answer is yes, explain what could be the reason. If you got sharp edges and fine details, explain what you did in order to achieve that.

Note: If you got blurry reconstructed images, just explain why. You dont need to change your code or retrain your model for better results (as long as your results can be interpreted as a human face).

Our Answer

Yes, we output blurry images. There could be several reasons for our results:

1) Low Latent Space - as discussed, since we saved computation time by choosing a low latent space we miss details in our training.

2) Gaussianity assumption - we assume the distribution is gaussian, yet analize it with "weak" encoder and decoder networks, that are not very deep. These networks might not be powerful enough to capture the variation in the data.

3) KL Divergence - is less sensitive to the detail of the data.

While there are methods to overcome these issues, a GAN will probably yield better, sharper results, and the two methods are often encorporated togather.

Question 6: Generate New Faces (10 %)

Now, for the fun part!

We are going to generate new celebrity faces with our VAE models. A function for new faces generation is given to you. Modify it (if needed) to fit your code.

```
# creates random noise sample in the correct shape.
def generate_faces(model, grid_size, latent):
    model.eval()
    dummy = torch.empty([grid_size,latent])
    z = torch.randn_like(dummy).to(device)

    #insert the random noise to the decoder to create new samples.
    sample = model.decode(z)
    new_face_list = []

    j=0
    while j < grid_size:
        
new_face_list.append(sample[j].cpu().detach().numpy().transpose(1,2,0)
)
        j+=1

    show(new_face_list)
```

Model 1 (L=3) results:

```
generate_faces(model_1,grid_size=32,latent=latent1)
```

Model 2 results:

```
generate_faces(model_2,grid_size=32,latent=latent2)
```

Q1: Generate new faces with VAE model with latent space dimension = 3. Did you get diverse results? What are the most prominent features that the latent space capture?

Q2: Generate new faces with VAE model with your decision for latent space dimension. What are the most prominent features that the latent space capture?

Q3: What are the differences? Your results are similar to the dataset images? Do you get realistic images for your chosen latent space dimension? If not, change your decision or your network to acheive more realistic results.

Our Answer

Q1 Answer

Our 32 generated images are all similar to each other, varying mostly in the blurry shape of the hair. Thr most prominent features that the latent space capture are the eyes and mouth, and general shape of the face.

Q2 Answer

These images are slightly more diverse. In some we can also see now the hair line, and more clearly the shape of the nose and hair. We also get more shadow and viewing angles.

Q3 Answer

The higher dimension did give us slightly more detailed images. These images are also brighter than the ones produced with a small dimension.

Our results are not very similar to the dataset images. When trying to train with a greater latent space we encounter a memory problem that can not be overcome with our version of google colab, so this resolution is what we make due with.

Question 7: Extrapolation (10 %)

Recall that we extrapolate in the images domain in Question 2, part (c). Here, extrapolate in the latent space domain to generate new images.

Define $\beta=[0,0.1,0.2,\ldots,0.9,1]$ and randomly sample from $Z\sim N(0,1)$ 2 different samples and generate 2 new face images: X_1, X_2.

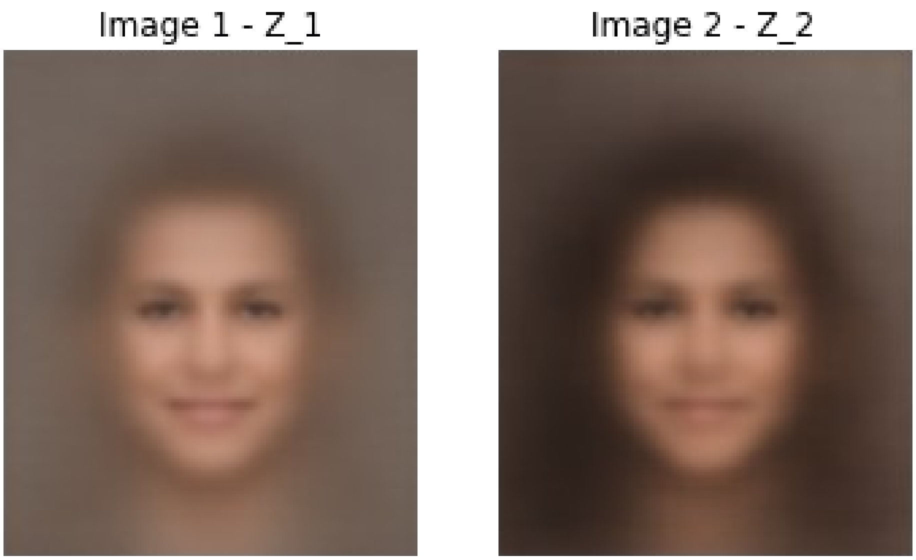
Extrapolate in the latent domain as follows: $\beta_i \cdot Z_1+(1-\beta_i)\cdot Z_2$ for each $\beta_i \in \beta$.

Plot the extrapolation of the images for each β and discuss your results. Repeat the process for 3 different samples.

```
# YOUR CODE GOES HERE
def Extrapolate(model, latent):
  model.eval()

  dummy1 = torch.empty([1,3])
  z1 = torch.randn_like(dummy1).to(device)
  dummy2 = torch.empty([1,3])
  z2 = torch.randn_like(dummy2).to(device)

  beta = (np.linspace(0, 1, 11)).tolist()
  image1 = model.decode(z1)
  image2 = model.decode(z2)
```

```
  fig, axes = plt.subplots(1,2)
  axes[0].imshow(image1.cpu().detach().numpy()[0].transpose(1,2,0))
  axes[0].set_title("Image 1 - Z_1")
  axes[0].axis('off')
  axes[1].imshow(image2.cpu().detach().numpy()[0].transpose(1,2,0))
  axes[1].set_title("Image 2 - Z_2")
  axes[1].axis('off')
  plt.show()

  for i in range(10):
    plt.subplot(2,5,i+1)
    combine = model.decode(beta[i]*z1+(1-beta[i])*z2) #b*z_1 +(1-b)*z_2
    plt.imshow(combine[0].cpu().permute(1,2,0).detach().numpy())
    plt.axis('off')
  plt.show()
```

```
model_1.eval()
for i in range(3):
    Extrapolate(model_1, latent=latent1)
```



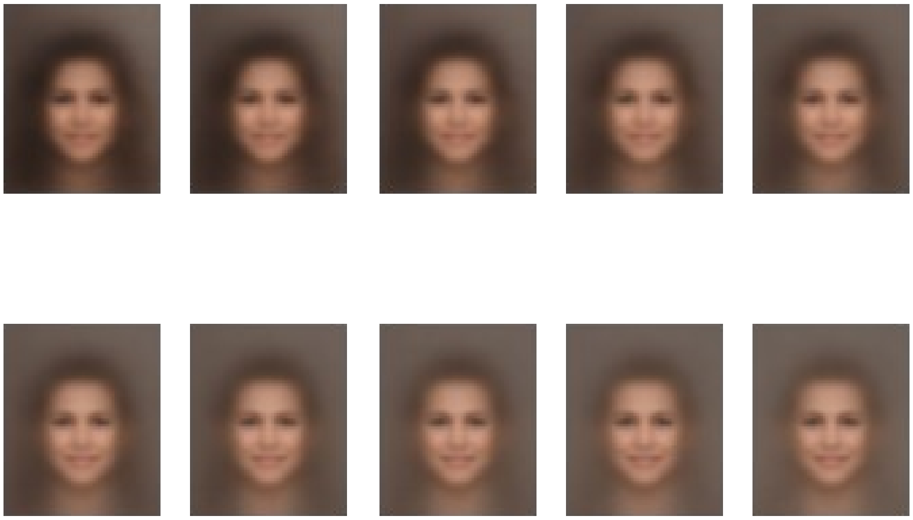
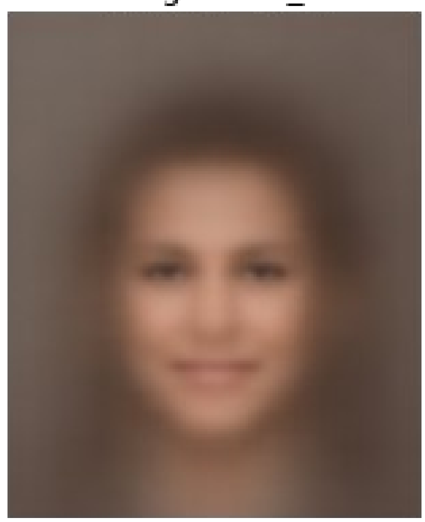
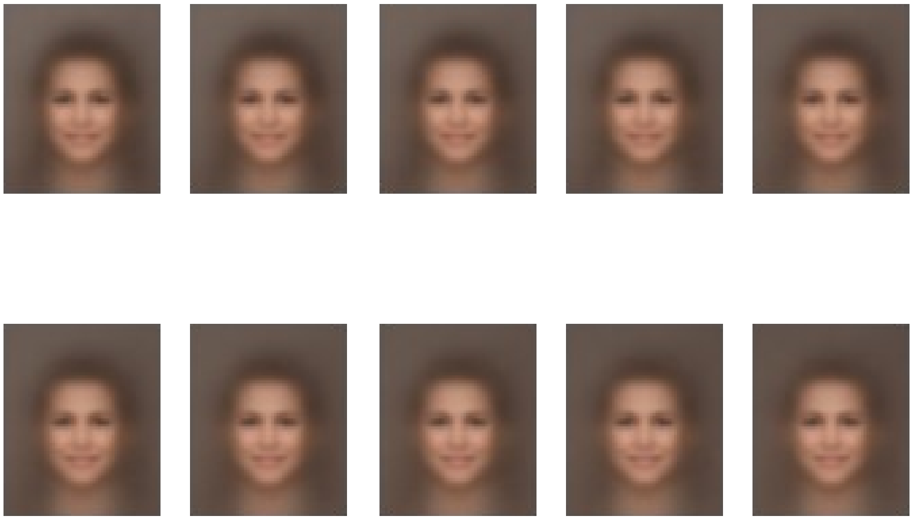


Image 1 - Z_1

Image 2 - Z_2





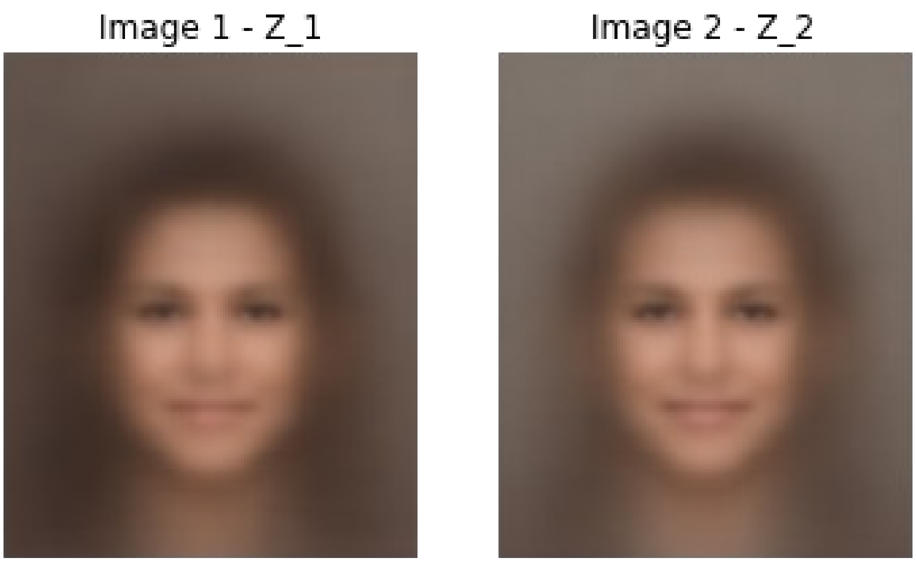
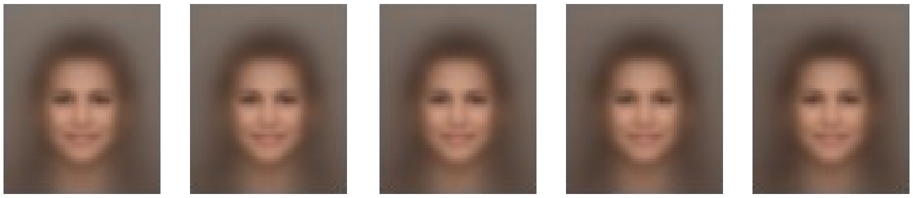


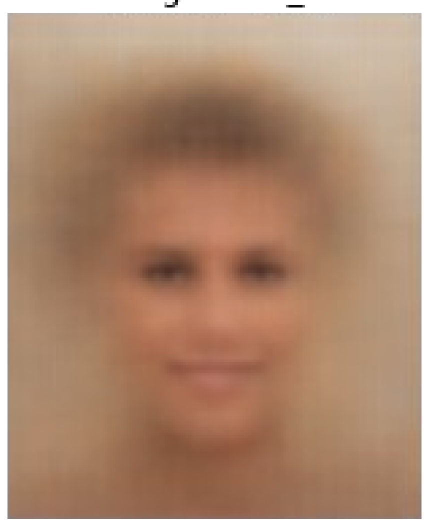
Image 1 - Z_1
Image 2 - Z_2



```
model_2.eval()
for i in range(3):
    Extrapolate(model_2, latent=latent2)
```

Image 1 - Z_1

Image 2 - Z_2



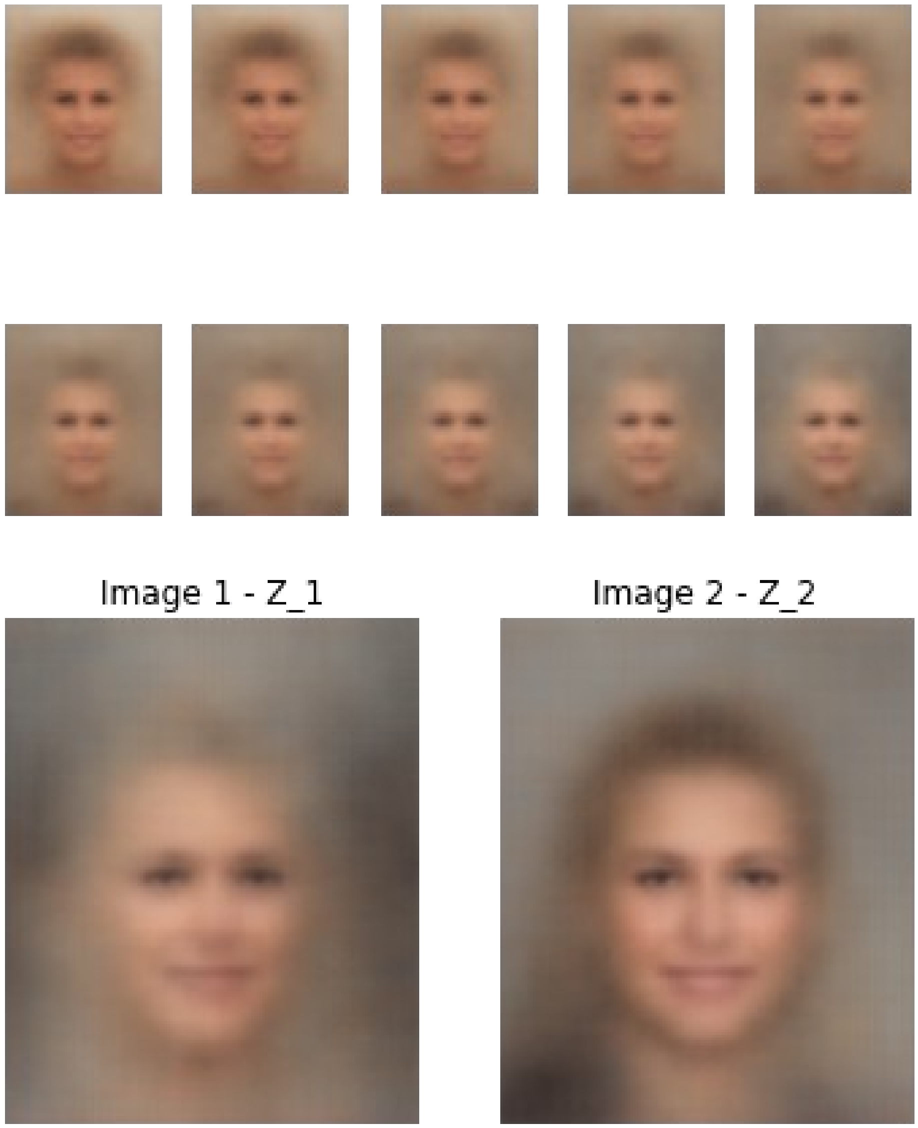
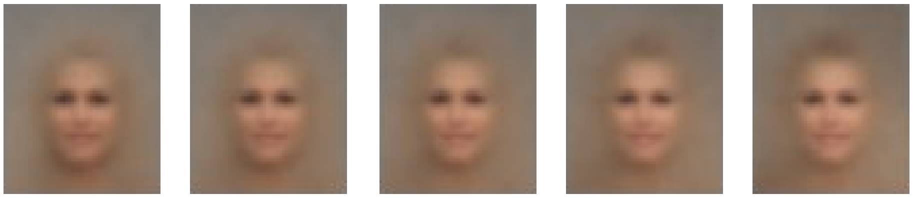
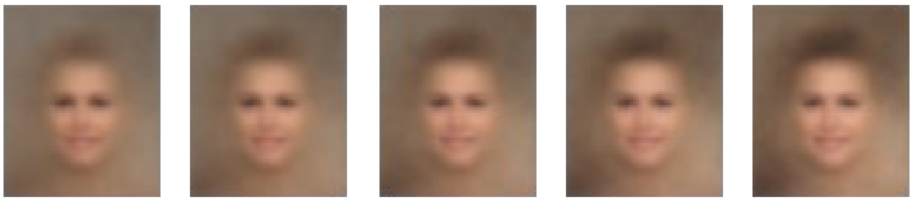


Image 1 - Z_1
Image 2 - Z_2

Image 1 - Z_1

Image 2 - Z_2





Our Answer

Since our starting images are blurred out, it's hard to tell how good the extrapulation results are. We do see a difference when changing β, indeed when $\beta=0$ or $\beta=1$ we see one of the images, and any number in between shows a slightly different image, varying from the first to second.