##Importing and preprocessing the dataset

```
from IPython import display

import glob
import imageio
import matplotlib.pyplot as plt
import numpy as np
import PIL
import tensorflow as tf
import tensorflow_probability as tfp
import time

(train_images, _), (test_images, _) =
tf.keras.datasets.mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
def preprocess_images(images):
  images = images.reshape((images.shape[0], 28, 28, 1)) / 255.
  return np.where(images > .5, 1.0, 0.0).astype('float32')

train_images = preprocess_images(train_images)
test_images = preprocess_images(test_images)

train_size = 60000
batch_size = 32
test_size = 10000

train_dataset = (tf.data.Dataset.from_tensor_slices(train_images)
                 .shuffle(train_size).batch(batch_size))
test_dataset = (tf.data.Dataset.from_tensor_slices(test_images)
                .shuffle(test_size).batch(batch_size))
```

##A. 1. Basic Vanilla VAE model implementation

```
class CVAE(tf.keras.Model):
  """Convolutional variational autoencoder."""

  def __init__(self, latent_dim):
    super(CVAE, self).__init__()
    self.latent_dim = latent_dim
    self.encoder = tf.keras.Sequential(
        [
            tf.keras.layers.InputLayer(input_shape=(28, 28, 1)),
            tf.keras.layers.Conv2D(
                filters=32, kernel_size=3, strides=(2, 2),
activation='relu'),
```

```
            tf.keras.layers.Conv2D(
                filters=64, kernel_size=3, strides=(2, 2),
activation='relu'),
            tf.keras.layers.Flatten(),
            # No activation
            tf.keras.layers.Dense(latent_dim + latent_dim),
        ]
    )

    self.decoder = tf.keras.Sequential(
        [
            tf.keras.layers.InputLayer(input_shape=(latent_dim,)),
            tf.keras.layers.Dense(units=7*7*32,
activation=tf.nn.relu),
            tf.keras.layers.Reshape(target_shape=(7, 7, 32)),
            tf.keras.layers.Conv2DTranspose(
                filters=64, kernel_size=3, strides=2, padding='same',
                activation='relu'),
            tf.keras.layers.Conv2DTranspose(
                filters=32, kernel_size=3, strides=2, padding='same',
                activation='relu'),
            # No activation
            tf.keras.layers.Conv2DTranspose(
                filters=1, kernel_size=3, strides=1, padding='same'),
        ]
    )

  @tf.function
  def sample(self, eps=None):
    if eps is None:
      eps = tf.random.normal(shape=(100, self.latent_dim))
    return self.decode(eps, apply_sigmoid=True)

  def encode(self, x):
    mean, logvar = tf.split(self.encoder(x), num_or_size_splits=2,
axis=1)
    return mean, logvar

  def reparameterize(self, mean, logvar):
    eps = tf.random.normal(shape=mean.shape)
    return eps * tf.exp(logvar * .5) + mean

  def decode(self, z, apply_sigmoid=False):
    logits = self.decoder(z)
    if apply_sigmoid:
      probs = tf.sigmoid(logits)
      return probs
    return logits
```

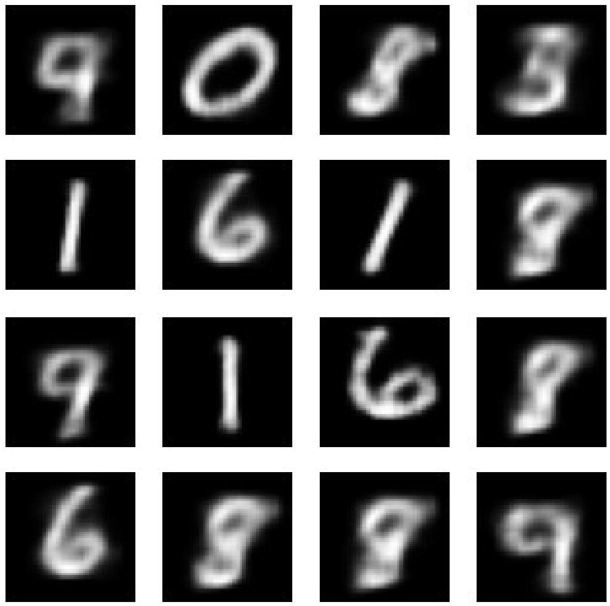
```
optimizer = tf.keras.optimizers.Adam(1e-4)


def log_normal_pdf(sample, mean, logvar, raxis=1):
  log2pi = tf.math.log(2. * np.pi)
  return tf.reduce_sum(
      -.5 * ((sample - mean) ** 2. * tf.exp(-logvar) + logvar +
log2pi),
      axis=raxis)


def compute_loss(model, x):
  mean, logvar = model.encode(x)
  z = model.reparameterize(mean, logvar)
  x_logit = model.decode(z)
  cross_ent = tf.nn.sigmoid_cross_entropy_with_logits(logits=x_logit,
labels=x)
  logpx_z = -tf.reduce_sum(cross_ent, axis=[1, 2, 3])
  logpz = log_normal_pdf(z, 0., 0.)
  logqz_x = log_normal_pdf(z, mean, logvar)
  return -tf.reduce_mean(logpx_z + logpz - logqz_x)


@tf.function
def train_step(model, x, optimizer):
  """Executes one training step and returns the loss.

  This function computes the loss and gradients, and uses the latter
to
  update the model's parameters.
  """
  with tf.GradientTape() as tape:
    loss = compute_loss(model, x)
  gradients = tape.gradient(loss, model.trainable_variables)
  optimizer.apply_gradients(zip(gradients, model.trainable_variables))

epochs = 10
# set the dimensionality of the latent space to a plane for
visualization later
latent_dim = 2
num_examples_to_generate = 16

# keeping the random vector constant for generation (prediction) so
# it will be easier to see the improvement.
random_vector_for_generation = tf.random.normal(
    shape=[num_examples_to_generate, latent_dim])
model = CVAE(latent_dim)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/
input_layer.py:26: UserWarning: Argument `input_shape` is deprecated.
```

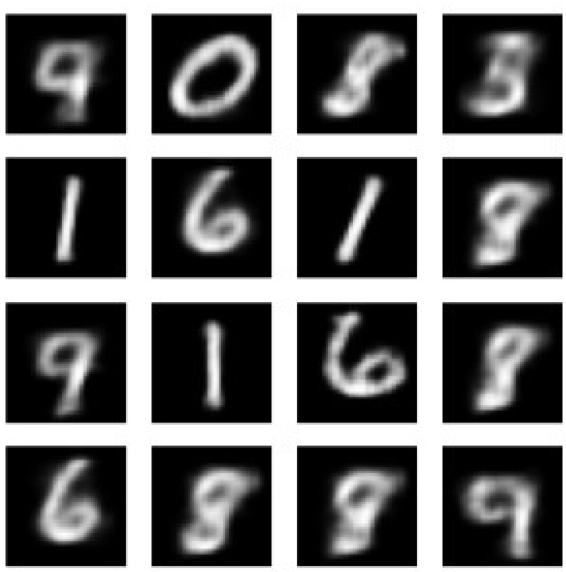
```
Use `shape` instead.
  warnings.warn(
```

```
def generate_and_save_images(model, epoch, test_sample):
  mean, logvar = model.encode(test_sample)
  z = model.reparameterize(mean, logvar)
  predictions = model.sample(z)
  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i + 1)
    plt.imshow(predictions[i, :, :, 0], cmap='gray')
    plt.axis('off')

  # tight_layout minimizes the overlap between 2 sub-plots
  plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
  plt.show()

# Pick a sample of the test set for generating output images
assert batch_size >= num_examples_to_generate
for test_batch in test_dataset.take(1):
  test_sample = test_batch[0:num_examples_to_generate, :, :, :]

generate_and_save_images(model, 0, test_sample)

for epoch in range(1, epochs + 1):
  start_time = time.time()
  for train_x in train_dataset:
    train_step(model, train_x, optimizer)
  end_time = time.time()

  loss = tf.keras.metrics.Mean()
  for test_x in test_dataset:
    loss(compute_loss(model, test_x))
  elbo = -loss.result()
  display.clear_output(wait=False)
  print('Epoch: {}, Test set ELBO: {}, time elapse for current epoch:
{}'
        .format(epoch, elbo, end_time - start_time))
  generate_and_save_images(model, epoch, test_sample)
```

```
Epoch: 10, Test set ELBO: -157.56301879882812, time elapse for current
epoch: 8.055445194244385
```



```
def display_image(epoch_no):
  return PIL.Image.open('image_at_epoch_{:04d}.png'.format(epoch_no))

plt.imshow(display_image(epoch))
plt.axis('off')  # Display images

(-0.5, 399.5, 399.5, -0.5)
```



```
anim_file = 'cvae1.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  image = imageio.imread(filename)
  writer.append_data(image)
```

```
<ipython-input-14-2c902c6cafcb>:7: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
<ipython-input-14-2c902c6cafcb>:9: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
```

```
!pip install git+https://github.com/tensorflow/docs
```

```
Collecting git+https://github.com/tensorflow/docs
  Cloning https://github.com/tensorflow/docs to /tmp/pip-req-build-
v0bm55hn
  Running command git clone --filter=blob:none --quiet
https://github.com/tensorflow/docs /tmp/pip-req-build-v0bm55hn
  Resolved https://github.com/tensorflow/docs to commit
460419a6369bd00bfc3ce7a7c92b0ca2a832c91b
  Preparing metadata (setup.py) ...  tensorflow-docs==2024.7.15.51478)
  Downloading astor-0.8.1-py2.py3-none-any.whl.metadata (4.2 kB)
Requirement already satisfied: absl-py in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
docs==2024.7.15.51478) (1.4.0)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
docs==2024.7.15.51478) (3.1.4)
Requirement already satisfied: nbformat in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
docs==2024.7.15.51478) (5.10.4)
Requirement already satisfied: protobuf>=3.12 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
docs==2024.7.15.51478) (3.20.3)
Requirement already satisfied: pyyaml in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
docs==2024.7.15.51478) (6.0.1)
```

```
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->tensorflow-
docs==2024.7.15.51478) (2.1.5)
Requirement already satisfied: fastjsonschema>=2.15 in
/usr/local/lib/python3.10/dist-packages (from nbformat->tensorflow-
docs==2024.7.15.51478) (2.20.0)
Requirement already satisfied: jsonschema>=2.6 in
/usr/local/lib/python3.10/dist-packages (from nbformat->tensorflow-
docs==2024.7.15.51478) (4.23.0)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in
/usr/local/lib/python3.10/dist-packages (from nbformat->tensorflow-
docs==2024.7.15.51478) (5.7.2)
Requirement already satisfied: traitlets>=5.1 in
/usr/local/lib/python3.10/dist-packages (from nbformat->tensorflow-
docs==2024.7.15.51478) (5.7.1)
Requirement already satisfied: attrs>=22.2.0 in
/usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6-
>nbformat->tensorflow-docs==2024.7.15.51478) (24.1.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in
/usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6-
>nbformat->tensorflow-docs==2024.7.15.51478) (2023.12.1)
Requirement already satisfied: referencing>=0.28.4 in
/usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6-
>nbformat->tensorflow-docs==2024.7.15.51478) (0.35.1)
Requirement already satisfied: rpds-py>=0.7.1 in
/usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6-
>nbformat->tensorflow-docs==2024.7.15.51478) (0.19.1)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core!
=5.0.*,>=4.12->nbformat->tensorflow-docs==2024.7.15.51478) (4.2.2)
Downloading astor-0.8.1-py2.py3-none-any.whl (27 kB)
Building wheels for collected packages: tensorflow-docs
  Building wheel for tensorflow-docs (setup.py) ... e=tensorflow_docs-
2024.7.15.51478-py3-none-any.whl size=182586
sha256=1e0bde080d37425fe41930fc303a226a9ad76383f56298bb485f52a7a371db7
d
  Stored in directory:
/tmp/pip-ephem-wheel-cache-axjk72k0/wheels/86/0f/1e/3b62293c8ffd0fd5a4
9508e6871cdb7554abe9c62afd35ec53
Successfully built tensorflow-docs
Installing collected packages: astor, tensorflow-docs
Successfully installed astor-0.8.1 tensorflow-docs-2024.7.15.51478
```

```python
import tensorflow_docs.vis.embed as embed
embed.embed_file(anim_file)
```

```
<IPython.core.display.HTML object>
```

##2. Changing the Encoder to an Encoder-Decoder Architecture

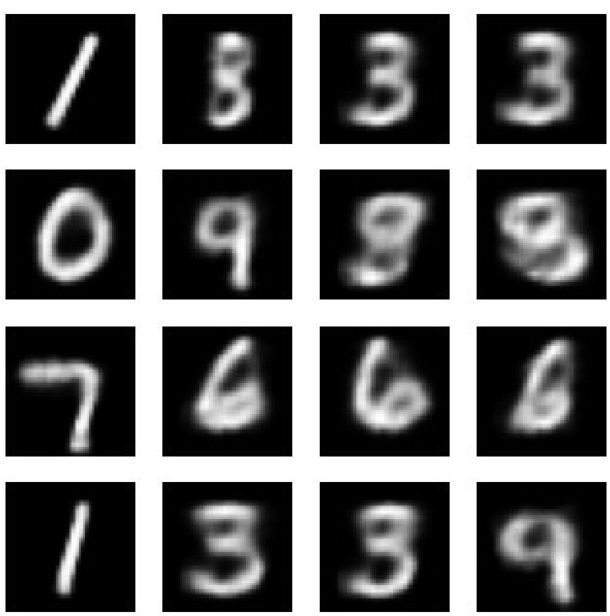
```python
class CVAE_2(tf.keras.Model):
    """VAE with Encoder-Decoder architecture as Encoder."""

    def __init__(self, latent_dim):
        super(CVAE_2, self).__init__()
        self.latent_dim = latent_dim

        # Encoder-Decoder architecture for the encoder part
        self.encoder_decoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(28, 28, 1)),
                # Downsampling
                tf.keras.layers.Conv2D(32, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(64, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(128, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(128, activation='relu'),
                # Bottleneck (latent space representation)
                tf.keras.layers.Dense(7 * 7 * 128, activation='relu'),
                tf.keras.layers.Reshape((7, 7, 128)),
                # Upsampling
                tf.keras.layers.Conv2DTranspose(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(32, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(1, 3, strides=1,
padding='same'),
                tf.keras.layers.Flatten(),
                # No activation for latent space
                tf.keras.layers.Dense(latent_dim + latent_dim)
            ]
        )

        # Decoder remains the same
        self.decoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(latent_dim,)),
                tf.keras.layers.Dense(units=7*7*32,
activation=tf.nn.relu),
                tf.keras.layers.Reshape(target_shape=(7, 7, 32)),
                tf.keras.layers.Conv2DTranspose(
                    filters=64, kernel_size=3, strides=2,
padding='same',
                    activation='relu'),
                tf.keras.layers.Conv2DTranspose(
```

```
                    filters=32, kernel_size=3, strides=2,
padding='same',
                    activation='relu'),
                # No activation
                tf.keras.layers.Conv2DTranspose(
                    filters=1, kernel_size=3, strides=1,
padding='same'),
            ]
        )

    def call(self, inputs):
        # Encode input to latent space
        encoded = self.encoder_decoder(inputs)
        # Split latent space into mean and log-variance
        mean, logvar = tf.split(encoded, num_or_size_splits=2, axis=1)
        return mean, logvar

    @tf.function
    def sample(self, eps=None):
        if eps is None:
            eps = tf.random.normal(shape=(100, self.latent_dim))
        return self.decode(eps, apply_sigmoid=True)

    def encode(self, x):
        mean, logvar = self.call(x)
        return mean, logvar

    def reparameterize(self, mean, logvar):
        eps = tf.random.normal(shape=tf.shape(mean))
        return eps * tf.exp(logvar * .5) + mean

    def decode(self, z, apply_sigmoid=False):
        logits = self.decoder(z)
        if apply_sigmoid:
            probs = tf.sigmoid(logits)
            return probs
        return logits

# Instantiate the model
latent_dim = 2
model = CVAE_2(latent_dim)

optimizer = tf.keras.optimizers.Adam(1e-4)


def log_normal_pdf(sample, mean, logvar, raxis=1):
  log2pi = tf.math.log(2. * np.pi)
  return tf.reduce_sum(
      -.5 * ((sample - mean) ** 2. * tf.exp(-logvar) + logvar +
log2pi),
```

```
      axis=raxis)


def compute_loss(model, x):
  mean, logvar = model.encode(x)
  z = model.reparameterize(mean, logvar)
  x_logit = model.decode(z)
  cross_ent = tf.nn.sigmoid_cross_entropy_with_logits(logits=x_logit,
labels=x)
  logpx_z = -tf.reduce_sum(cross_ent, axis=[1, 2, 3])
  logpz = log_normal_pdf(z, 0., 0.)
  logqz_x = log_normal_pdf(z, mean, logvar)
  return -tf.reduce_mean(logpx_z + logpz - logqz_x)


@tf.function
def train_step(model, x, optimizer):
  """Executes one training step and returns the loss.

  This function computes the loss and gradients, and uses the latter
to
  update the model's parameters.
  """
  with tf.GradientTape() as tape:
    loss = compute_loss(model, x)
  gradients = tape.gradient(loss, model.trainable_variables)
  optimizer.apply_gradients(zip(gradients, model.trainable_variables))

epochs = 10
# set the dimensionality of the latent space to a plane for
visualization later
latent_dim = 2
num_examples_to_generate = 16

# keeping the random vector constant for generation (prediction) so
# it will be easier to see the improvement.
random_vector_for_generation = tf.random.normal(
    shape=[num_examples_to_generate, latent_dim])
model = CVAE_2(latent_dim)

def generate_and_save_images_2(model, epoch, test_sample):
  mean, logvar = model.encode(test_sample)
  z = model.reparameterize(mean, logvar)
  predictions = model.sample(z)
  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i + 1)
    plt.imshow(predictions[i, :, :, 0], cmap='gray')
    plt.axis('off')
```

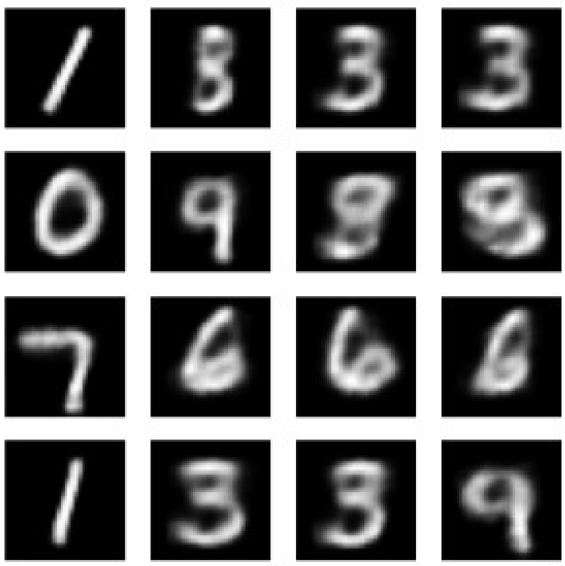
```
  # tight_layout minimizes the overlap between 2 sub-plots
  plt.savefig('image_2_at_epoch_{:04d}.png'.format(epoch))
  plt.show()

# Pick a sample of the test set for generating output images
assert batch_size >= num_examples_to_generate
for test_batch in test_dataset.take(1):
  test_sample = test_batch[0:num_examples_to_generate, :, :, :]

generate_and_save_images_2(model, 0, test_sample)

for epoch in range(1, epochs + 1):
  start_time = time.time()
  for train_x in train_dataset:
    train_step(model, train_x, optimizer)
  end_time = time.time()

  loss = tf.keras.metrics.Mean()
  for test_x in test_dataset:
    loss(compute_loss(model, test_x))
  elbo = -loss.result()
  display.clear_output(wait=False)
  print('Epoch: {}, Test set ELBO: {}, time elapse for current epoch:
{}'
        .format(epoch, elbo, end_time - start_time))
  generate_and_save_images_2(model, epoch, test_sample)
```

```
Epoch: 10, Test set ELBO: -145.325927734375, time elapse for current
epoch: 17.4734308719635
```



```
def display_image_2(epoch_no):
  return
PIL.Image.open('image_2_at_epoch_{:04d}.png'.format(epoch_no))

plt.imshow(display_image_2(epoch))
plt.axis('off')  # Display images
```

```
(-0.5, 399.5, 399.5, -0.5)
```



```
anim_file = 'cvae2.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image_2*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  image = imageio.imread(filename)
  writer.append_data(image)
```

```
<ipython-input-25-f2399fed895a>:7: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
<ipython-input-25-f2399fed895a>:9: DeprecationWarning: Starting with
```

```
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
```

##3. Changing the Decoder to an Encoder-Decoder Architecture

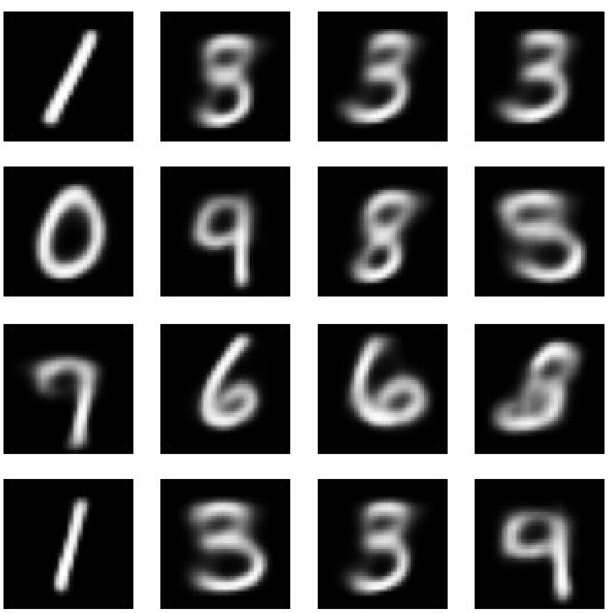
```
class CVAE_3(tf.keras.Model):
    """VAE with vanilla encoder and Encoder-Decoder architecture as
Decoder."""

    def __init__(self, latent_dim):
        super(CVAE_3, self).__init__()
        self.latent_dim = latent_dim

        # Vanilla encoder
        self.encoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(28, 28, 1)),
                tf.keras.layers.Conv2D(32, 3, strides=(2, 2),
activation='relu'),
                tf.keras.layers.Conv2D(64, 3, strides=(2, 2),
activation='relu'),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(128, activation='relu'),
                # No activation for latent space
                tf.keras.layers.Dense(latent_dim + latent_dim)
            ]
        )

        # Encoder-Decoder architecture for the decoder part
        self.decoder_encoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(latent_dim,)),
                tf.keras.layers.Dense(units=7 * 7 * 32,
activation='relu'),
                tf.keras.layers.Reshape(target_shape=(7, 7, 32)),
                # Downsampling
                tf.keras.layers.Conv2D(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(128, activation='relu'),
                # Bottleneck (latent space representation)
                tf.keras.layers.Dense(7 * 7 * 128, activation='relu'),
                tf.keras.layers.Reshape((7, 7, 128)),
                # Upsampling
```

```
                tf.keras.layers.Conv2DTranspose(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(32, 3, strides=1,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(1, 3, strides=1,
padding='same')
            ]
        )

    def call(self, inputs):
        # Encode input to latent space
        encoded = self.encoder(inputs)
        # Split latent space into mean and log-variance
        mean, logvar = tf.split(encoded, num_or_size_splits=2, axis=1)
        return mean, logvar

    @tf.function
    def sample(self, eps=None):
        if eps is None:
            eps = tf.random.normal(shape=(100, self.latent_dim))
        return self.decode(eps, apply_sigmoid=True)

    def encode(self, x):
        mean, logvar = self.call(x)
        return mean, logvar

    def reparameterize(self, mean, logvar):
        eps = tf.random.normal(shape=tf.shape(mean))
        return eps * tf.exp(logvar * .5) + mean

    def decode(self, z, apply_sigmoid=False):
        logits = self.decoder_encoder(z)
        if apply_sigmoid:
            probs = tf.sigmoid(logits)
            return probs
        return logits

# Instantiate the model
latent_dim = 2
model = CVAE_3(latent_dim)

optimizer = tf.keras.optimizers.Adam(1e-4)


def log_normal_pdf(sample, mean, logvar, raxis=1):
  log2pi = tf.math.log(2. * np.pi)
  return tf.reduce_sum(
      -.5 * ((sample - mean) ** 2. * tf.exp(-logvar) + logvar +
```

```
log2pi),
      axis=raxis)


def compute_loss(model, x):
  mean, logvar = model.encode(x)
  z = model.reparameterize(mean, logvar)
  x_logit = model.decode(z)
  cross_ent = tf.nn.sigmoid_cross_entropy_with_logits(logits=x_logit,
labels=x)
  logpx_z = -tf.reduce_sum(cross_ent, axis=[1, 2, 3])
  logpz = log_normal_pdf(z, 0., 0.)
  logqz_x = log_normal_pdf(z, mean, logvar)
  return -tf.reduce_mean(logpx_z + logpz - logqz_x)


@tf.function
def train_step(model, x, optimizer):
  """Executes one training step and returns the loss.

  This function computes the loss and gradients, and uses the latter
to
  update the model's parameters.
  """
  with tf.GradientTape() as tape:
    loss = compute_loss(model, x)
  gradients = tape.gradient(loss, model.trainable_variables)
  optimizer.apply_gradients(zip(gradients, model.trainable_variables))

epochs = 10
# set the dimensionality of the latent space to a plane for
visualization later
latent_dim = 2
num_examples_to_generate = 16

# keeping the random vector constant for generation (prediction) so
# it will be easier to see the improvement.
random_vector_for_generation = tf.random.normal(
    shape=[num_examples_to_generate, latent_dim])
model = CVAE_3(latent_dim)

def generate_and_save_images_3(model, epoch, test_sample):
  mean, logvar = model.encode(test_sample)
  z = model.reparameterize(mean, logvar)
  predictions = model.sample(z)
  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i + 1)
    plt.imshow(predictions[i, :, :, 0], cmap='gray')
```

```
    plt.axis('off')

  # tight_layout minimizes the overlap between 2 sub-plots
  plt.savefig('image_3_at_epoch_{:04d}.png'.format(epoch))
  plt.show()

generate_and_save_images_3(model, 0, test_sample)

for epoch in range(1, epochs + 1):
  start_time = time.time()
  for train_x in train_dataset:
    train_step(model, train_x, optimizer)
  end_time = time.time()

  loss = tf.keras.metrics.Mean()
  for test_x in test_dataset:
    loss(compute_loss(model, test_x))
  elbo = -loss.result()
  display.clear_output(wait=False)
  print('Epoch: {}, Test set ELBO: {}, time elapse for current epoch:
{}'
        .format(epoch, elbo, end_time - start_time))
  generate_and_save_images_3(model, epoch, test_sample)
```

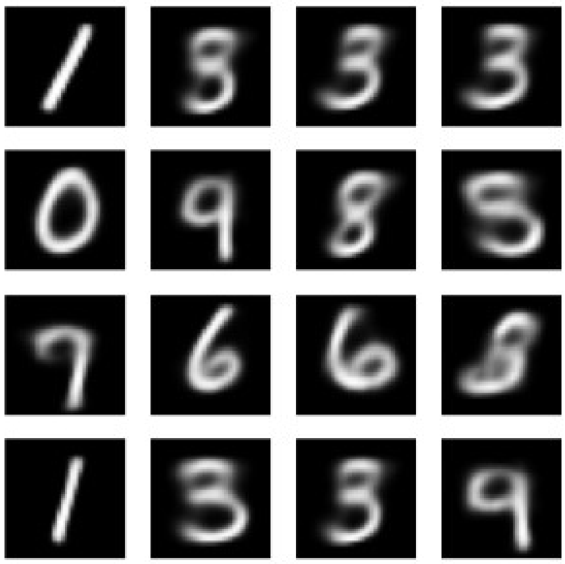
```
Epoch: 10, Test set ELBO: -142.83706665039062, time elapse for current
epoch: 13.64205527305603
```



```
def display_image_3(epoch_no):
  return
PIL.Image.open('image_3_at_epoch_{:04d}.png'.format(epoch_no))
```

```
plt.imshow(display_image_3(epoch))
plt.axis('off')  # Display images
```

```
(-0.5, 399.5, 399.5, -0.5)
```



```
anim_file = 'cvae3.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image_3*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  image = imageio.imread(filename)
  writer.append_data(image)
```

```
<ipython-input-43-c53a5a2e94f7>:7: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
<ipython-input-43-c53a5a2e94f7>:9: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
```

```
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
```

##4. Changing both the Encoder and Decoder to an Encoder-Decoder Architecture

```
class CVAE_4(tf.keras.Model):
    """VAE with Encoder-Decoder architectures for both Encoder and
Decoder."""

    def __init__(self, latent_dim):
        super(CVAE_4, self).__init__()
        self.latent_dim = latent_dim

        # Encoder-Decoder architecture for the encoder part
        self.encoder_decoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(28, 28, 1)),
                # Downsampling
                tf.keras.layers.Conv2D(32, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(64, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(128, 3, strides=(2, 2),
activation='relu', padding='same'),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(128, activation='relu'),
                # Bottleneck (latent space representation)
                tf.keras.layers.Dense(7 * 7 * 128, activation='relu'),
                tf.keras.layers.Reshape((7, 7, 128)),
                # Upsampling
                tf.keras.layers.Conv2DTranspose(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(32, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(1, 3, strides=1,
padding='same'),
                tf.keras.layers.Flatten(),
                # No activation for latent space
                tf.keras.layers.Dense(latent_dim + latent_dim)
            ]
        )

        # Encoder-Decoder architecture for the decoder part
        self.decoder_encoder = tf.keras.Sequential(
            [
                tf.keras.layers.InputLayer(input_shape=(latent_dim,)),
                tf.keras.layers.Dense(units=7 * 7 * 32,
```

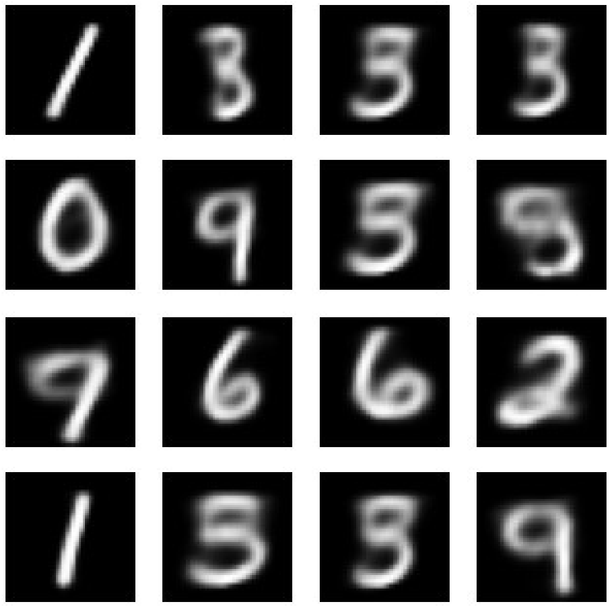
```
activation='relu'),
                tf.keras.layers.Reshape(target_shape=(7, 7, 32)),
                # Downsampling
                tf.keras.layers.Conv2D(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2D(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(128, activation='relu'),
                # Bottleneck (latent space representation)
                tf.keras.layers.Dense(7 * 7 * 128, activation='relu'),
                tf.keras.layers.Reshape((7, 7, 128)),
                # Upsampling
                tf.keras.layers.Conv2DTranspose(128, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(64, 3, strides=2,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(32, 3, strides=1,
activation='relu', padding='same'),
                tf.keras.layers.Conv2DTranspose(1, 3, strides=1,
padding='same')
            ]
        )

    def call(self, inputs):
        # Encode input to latent space
        encoded = self.encoder_decoder(inputs)
        # Split latent space into mean and log-variance
        mean, logvar = tf.split(encoded, num_or_size_splits=2, axis=1)
        return mean, logvar

    @tf.function
    def sample(self, eps=None):
        if eps is None:
            eps = tf.random.normal(shape=(100, self.latent_dim))
        return self.decode(eps, apply_sigmoid=True)

    def encode(self, x):
        mean, logvar = self.call(x)
        return mean, logvar

    def reparameterize(self, mean, logvar):
        eps = tf.random.normal(shape=tf.shape(mean))
        return eps * tf.exp(logvar * .5) + mean

    def decode(self, z, apply_sigmoid=False):
        logits = self.decoder_encoder(z)
        if apply_sigmoid:
            probs = tf.sigmoid(logits)
            return probs
```

```python
        return logits

# Instantiate the model
latent_dim = 2
model = CVAE_4(latent_dim)

epochs = 10
# set the dimensionality of the latent space to a plane for
visualization later
latent_dim = 2
num_examples_to_generate = 16

# keeping the random vector constant for generation (prediction) so
# it will be easier to see the improvement.
random_vector_for_generation = tf.random.normal(
    shape=[num_examples_to_generate, latent_dim])
model = CVAE_4(latent_dim)

def generate_and_save_images_4(model, epoch, test_sample):
  mean, logvar = model.encode(test_sample)
  z = model.reparameterize(mean, logvar)
  predictions = model.sample(z)
  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i + 1)
    plt.imshow(predictions[i, :, :, 0], cmap='gray')
    plt.axis('off')

  # tight_layout minimizes the overlap between 2 sub-plots
  plt.savefig('image_4_at_epoch_{:04d}.png'.format(epoch))
  plt.show()

optimizer = tf.keras.optimizers.Adam(1e-4)


def log_normal_pdf(sample, mean, logvar, raxis=1):
  log2pi = tf.math.log(2. * np.pi)
  return tf.reduce_sum(
      -.5 * ((sample - mean) ** 2. * tf.exp(-logvar) + logvar +
log2pi),
      axis=raxis)


def compute_loss(model, x):
  mean, logvar = model.encode(x)
  z = model.reparameterize(mean, logvar)
  x_logit = model.decode(z)
  cross_ent = tf.nn.sigmoid_cross_entropy_with_logits(logits=x_logit,
labels=x)
  logpx_z = -tf.reduce_sum(cross_ent, axis=[1, 2, 3])
```

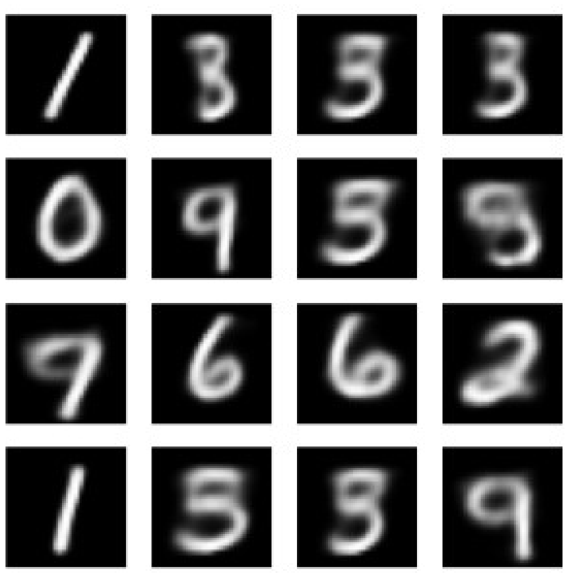
```python
  logpz = log_normal_pdf(z, 0., 0.)
  logqz_x = log_normal_pdf(z, mean, logvar)
  return -tf.reduce_mean(logpx_z + logpz - logqz_x)


@tf.function
def train_step(model, x, optimizer):
  """Executes one training step and returns the loss.

  This function computes the loss and gradients, and uses the latter
to
  update the model's parameters.
  """
  with tf.GradientTape() as tape:
    loss = compute_loss(model, x)
  gradients = tape.gradient(loss, model.trainable_variables)
  optimizer.apply_gradients(zip(gradients, model.trainable_variables))
```

```python
generate_and_save_images_4(model, 0, test_sample)

for epoch in range(1, epochs + 1):
  start_time = time.time()
  for train_x in train_dataset:
    train_step(model, train_x, optimizer)
  end_time = time.time()

  loss = tf.keras.metrics.Mean()
  for test_x in test_dataset:
    loss(compute_loss(model, test_x))
  elbo = -loss.result()
  display.clear_output(wait=False)
  print('Epoch: {}, Test set ELBO: {}, time elapse for current epoch:
{}'
        .format(epoch, elbo, end_time - start_time))
  generate_and_save_images_4(model, epoch, test_sample)
```

```
Epoch: 10, Test set ELBO: -140.47776794433594, time elapse for current
epoch: 24.610986471176147
```



```
def display_image_4(epoch_no):
  return
PIL.Image.open('image_4_at_epoch_{:04d}.png'.format(epoch_no))

plt.imshow(display_image_4(epoch))
plt.axis('off')  # Display images

(-0.5, 399.5, 399.5, -0.5)
```



```
anim_file = 'cvae4.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image_4*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  image = imageio.imread(filename)
  writer.append_data(image)
```

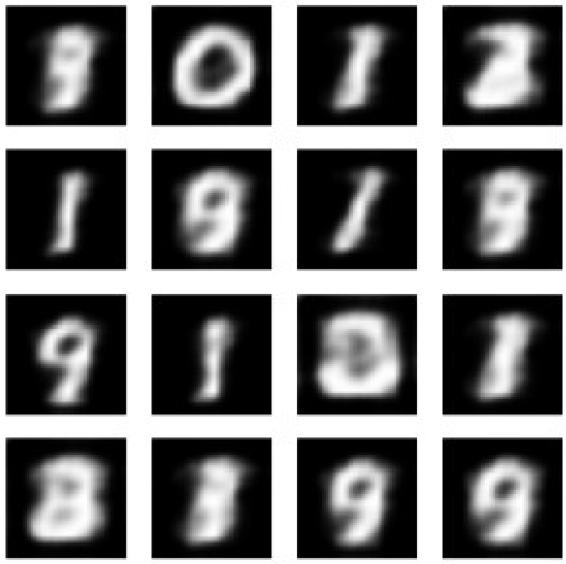
```
<ipython-input-62-b070b0b1f2ee>:7: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
<ipython-input-62-b070b0b1f2ee>:9: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
```

##Comparing Results

At Epoch 1 -

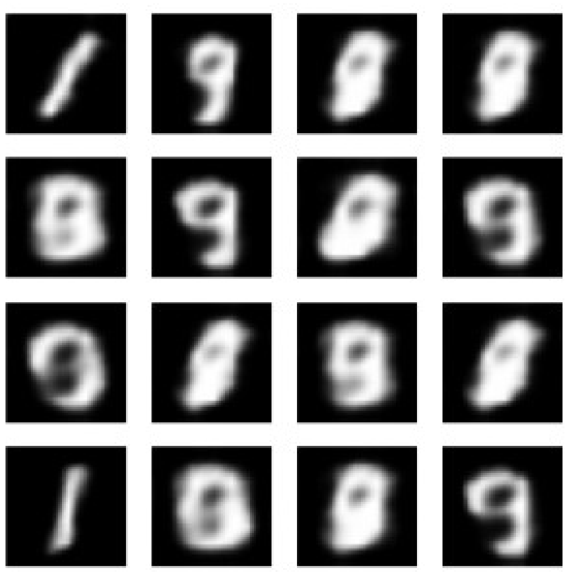
```
plt.imshow(display_image(1))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



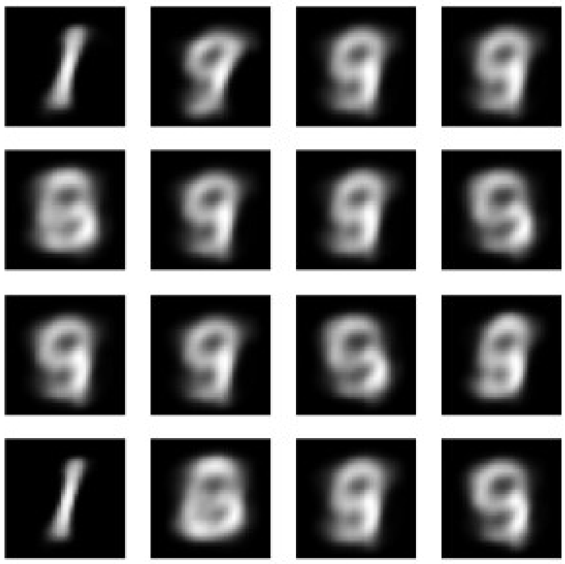
```
plt.imshow(display_image_2(1))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



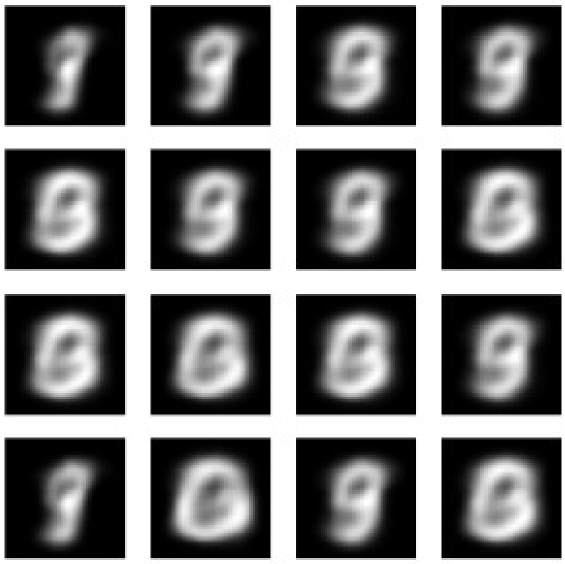
```
plt.imshow(display_image_3(1))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



```
plt.imshow(display_image_4(1))
plt.axis('off')
```

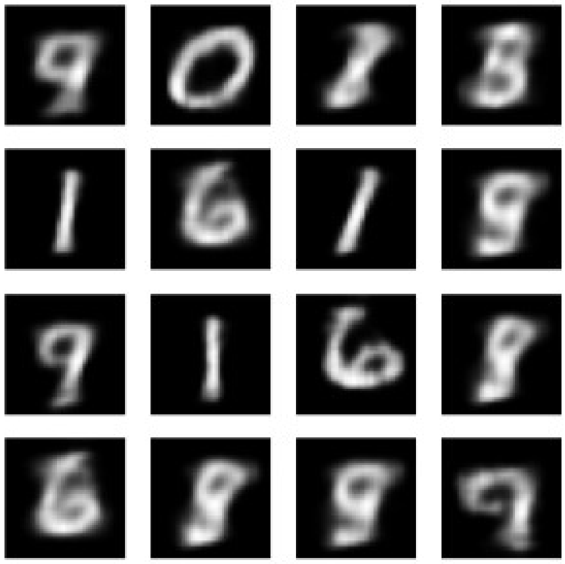
```
(-0.5, 399.5, 399.5, -0.5)
```



At epoch 5 -

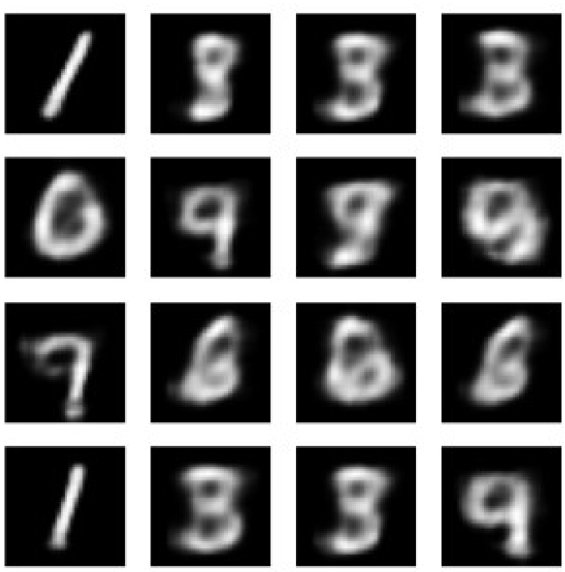
```
plt.imshow(display_image(5))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



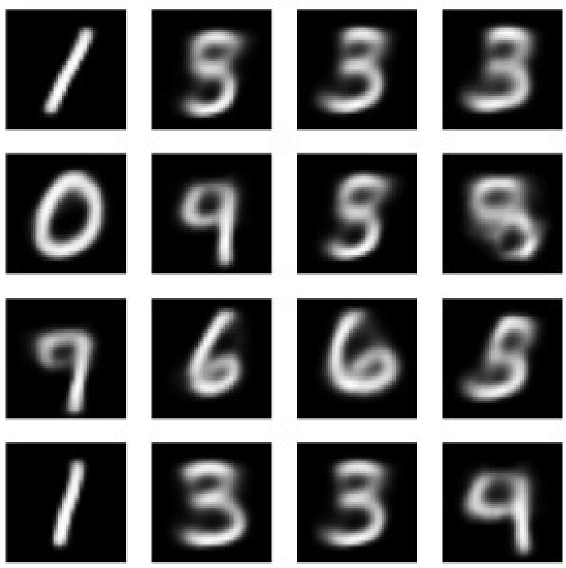
```
plt.imshow(display_image_2(5))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



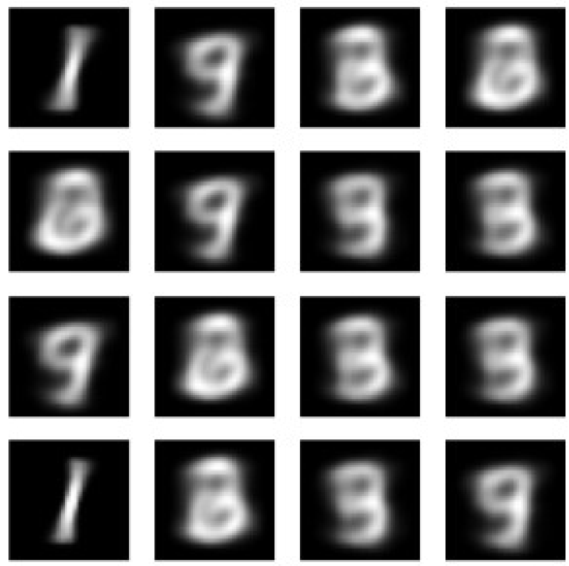
```
plt.imshow(display_image_3(5))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



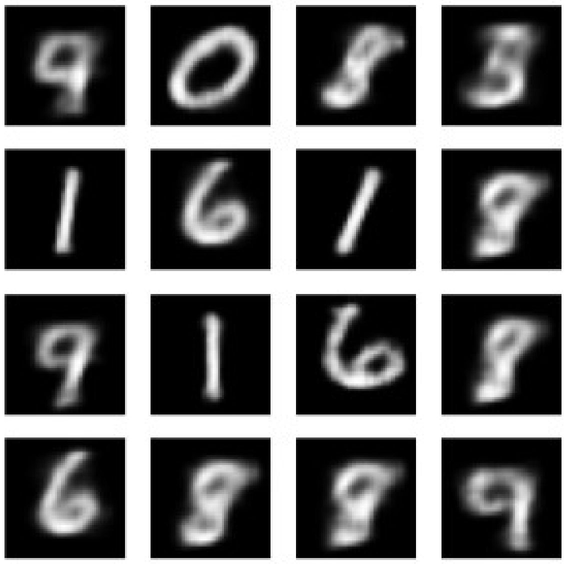
```
plt.imshow(display_image_4(5))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



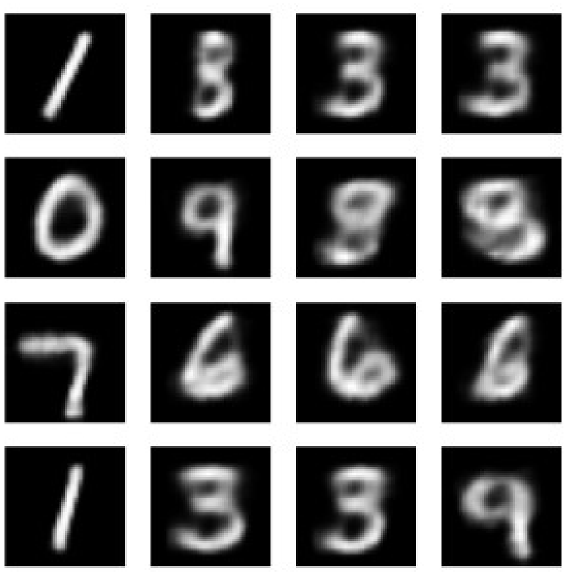
At epoch 10 -

```
plt.imshow(display_image(10))
plt.axis('off')

(-0.5, 399.5, 399.5, -0.5)
```



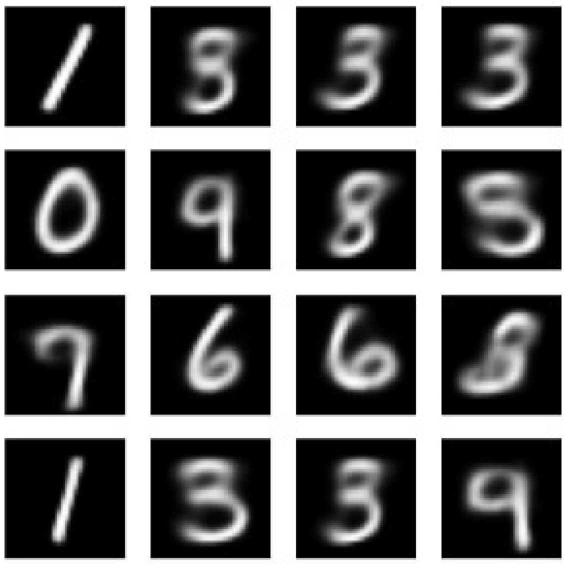
```
plt.imshow(display_image_2(10))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



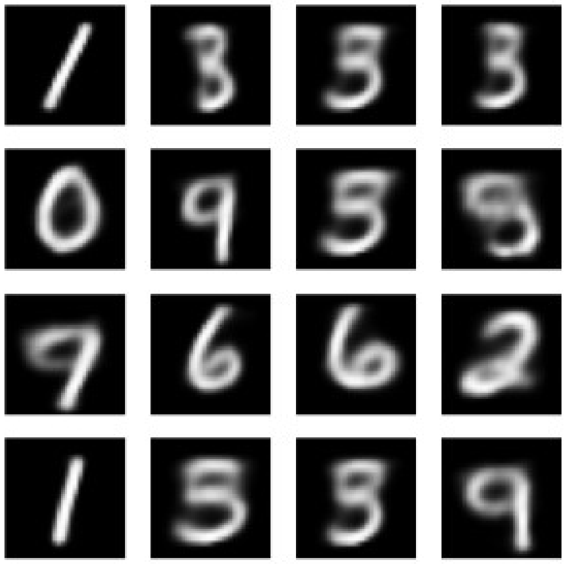
```
plt.imshow(display_image_3(10))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



```
plt.imshow(display_image_4(10))
plt.axis('off')
```

```
(-0.5, 399.5, 399.5, -0.5)
```



Comparing the Gifs -

```
import tensorflow_docs.vis.embed as embed
embed.embed_file('cvae1.gif')

<IPython.core.display.HTML object>

embed.embed_file('cvae2.gif')

<IPython.core.display.HTML object>

embed.embed_file('cvae3.gif')

<IPython.core.display.HTML object>

embed.embed_file('cvae4.gif')

<IPython.core.display.HTML object>
```

The best architecture was the fourth one (VAE with Encoder-Decoder on both sides). It turned out to be the best in terms of both accuracy and output image quality. The complex structures on both the encoder and decoder sides enabled better feature extraction and image reconstruction.

The second and third architectures performed better than the original VAE but had trade-offs depending on whether the complexity was in the encoder or decoder.

The original VAE served as a good starting point but was outperformed by the more complex variants.