Denoising Diffusion Probabilistic Model

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In this lab, we introduce the Denoising Diffusion Probabilistic Models (DDPMs), which is one of the implementations to demonstrate the usage of the diffusion model generating images, and as an example, dataset Oxford Flowers 102 are used for training the model to generate the images of flower.

Introduction to the diffusion model

Generative modeling experienced tremendous growth in the last five years. Models like VAEs, GANs, and flow-based models proved to be a great success in generating high-quality content, especially images. Diffusion models are a new type of generative model that has proven to be better than previous approaches.

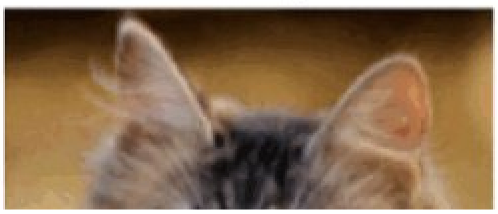
Diffusion models are inspired by non-equilibrium thermodynamics, and they learn to generate by denoising. Learning by denoising consists of two processes, each of which is a Markov Chain. These are:

1. The forward process: In the forward process, we slowly add random noise to the data in a series of time steps `(t1, t2, ..., tn )`. Samples at the current time step are drawn from a Gaussian distribution where the mean of the distribution is conditioned on the sample at the previous time step, and the variance of the distribution follows a fixed schedule. At the end of the forward process, the samples end up with a pure noise distribution.

2. The reverse process: During the reverse process, we try to undo the added noise at every time step. We start with the pure noise distribution (the last step of the forward process) and try to denoise the samples in the backward direction `(tn, tn-1, ..., t1)`.

We implement the Denoising Diffusion Probabilistic Models paper or DDPMs for short in this code example. It was the first paper demonstrating the use of diffusion models for generating high-quality images. The authors proved that a certain parameterization of diffusion models reveals an equivalence with denoising score matching over multiple noise levels during training and with annealed Langevin dynamics during sampling that generates the best quality results.

This paper replicates both the Markov chains (forward process and reverse process) involved in the diffusion process but for images. The forward process is fixed and gradually adds Gaussian noise to the images according to a fixed variance schedule denoted by beta in the paper. This is what the diffusion process looks like in case of images: (image -> noise::noise -> image)



The paper describes two algorithms, one for training the model, and the other for sampling from the trained model. Training is performed by optimizing the usual variational bound on negative log-likelihood. The objective function is further simplified, and the network is treated as a noise prediction network. Once optimized, we can sample from the network to generate new images from noise samples. Here is an overview of both algorithms as presented in the paper:

Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \mathrm{Uniform}(\{1, \ldots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \ldots, 1$ **do**
3: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

Note: DDPM is just one way of implementing a diffusion model. Also, the sampling algorithm in the DDPM replicates the complete Markov chain. Hence, it's slow in generating new samples compared to other generative models like GANs. Lots of research efforts have been made to address this issue. One such example is Denoising Diffusion Implicit Models, or DDIM for short, where the authors replaced the Markov chain with a non-Markovian process to sample faster. You can find the code example for DDIM here

Implementing a DDPM model is simple. We define a model that takes two inputs: Images and the randomly sampled time steps. At each training step, we perform the following operations to train our model:

1. Sample random noise to be added to the inputs.
2. Apply the forward process to diffuse the inputs with the sampled noise.
3. Your model takes these noisy samples as inputs and outputs the noise prediction for each time step.
4. Given true noise and predicted noise, we calculate the loss values
5. We then calculate the gradients and update the model weights.

Given that our model knows how to denoise a noisy sample at a given time step, we can leverage this idea to generate new samples, starting from a pure noise distribution.

Setup

Please check on the TensorFlow Addons (TFA) Installation for compatibility with your version before installing the tensorflow_addons.

In [ ]:

```
import math
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import tensorflow_addons as tfa
```

Hyperparameters

In [ ]:

```
batch_size = 32
num_epochs = 1  # Just for the sake of demonstration
total_timesteps = 1000
norm_groups = 8  # Number of groups used in GroupNormalization layer
learning_rate = 2e-4

img_size = 64
img_channels = 3
clip_min = -1.0
clip_max = 1.0

first_conv_channels = 64
channel_multiplier = [1, 2, 4, 8]
widths = [first_conv_channels * mult for mult in channel_multiplier]
has_attention = [False, False, True, True]
num_res_blocks = 2  # Number of residual blocks

dataset_name = "oxford_flowers102"
splits = ["train"]
```

Dataset

We use the Oxford Flowers 102 dataset for generating images of flowers. In terms of preprocessing, we use center cropping for resizing the images to the desired image size, and we rescale the pixel values in the range `[-1.0, 1.0]`. This is in line with the range of the pixel values that was applied by the authors of the DDPMs paper. For augmenting training data, we randomly flip the images left/right.

In [ ]:

```
# Load the dataset
(ds,) = tfds.load(dataset_name, split=splits, with_info=False, shuffle_files=True)


def augment(img):
    """Flips an image left/right randomly."""
    return tf.image.random_flip_left_right(img)


def resize_and_rescale(img, size):
    """Resize the image to the desired size first and then
    rescale the pixel values in the range [-1.0, 1.0].

    Args:
        img: Image tensor
```

```
        size: Desired image size for resizing
    Returns:
        Resized and rescaled image tensor
    """

    height = tf.shape(img)[0]
    width = tf.shape(img)[1]
    crop_size = tf.minimum(height, width)

    img = tf.image.crop_to_bounding_box(
        img,
        (height - crop_size) // 2,
        (width - crop_size) // 2,
        crop_size,
        crop_size,
    )

    # Resize
    img = tf.cast(img, dtype=tf.float32)
    img = tf.image.resize(img, size=size, antialias=True)

    # Rescale the pixel values
    img = img / 127.5 - 1.0
    img = tf.clip_by_value(img, clip_min, clip_max)
    return img


def train_preprocessing(x):
    img = x["image"]
    img = resize_and_rescale(img, size=(img_size, img_size))
    img = augment(img)
    return img


train_ds = (
    ds.map(train_preprocessing, num_parallel_calls=tf.data.AUTOTUNE)
    .batch(batch_size, drop_remainder=True)
    .shuffle(batch_size * 2)
    .prefetch(tf.data.AUTOTUNE)
)
```

```
Downloading and preparing dataset 328.90 MiB (download: 328.90 MiB, generated: 331.34 Mi
B, total: 660.25 MiB) to /root/tensorflow_datasets/oxford_flowers102/2.1.1...
```

```
Dataset oxford_flowers102 downloaded and prepared to /root/tensorflow_datasets/oxford_fl
owers102/2.1.1. Subsequent calls will reuse this data.
```

Gaussian diffusion utilities

We define the forward process and the reverse process as a separate utility. Most of the code in this utility has been borrowed from the original implementation with some slight modifications.

In [ ]:

```
class GaussianDiffusion:
    """Gaussian diffusion utility.
```

```
    Args:
        beta_start: Start value of the scheduled variance
        beta_end: End value of the scheduled variance
        timesteps: Number of time steps in the forward process
    """

    def __init__(
        self,
        beta_start=1e-4,
        beta_end=0.02,
        timesteps=1000,
        clip_min=-1.0,
        clip_max=1.0,
    ):
        self.beta_start = beta_start
        self.beta_end = beta_end
        self.timesteps = timesteps
        self.clip_min = clip_min
        self.clip_max = clip_max

        # Define the linear variance schedule
        self.betas = betas = np.linspace(
            beta_start,
            beta_end,
            timesteps,
            dtype=np.float64,  # Using float64 for better precision
        )
        self.num_timesteps = int(timesteps)

        alphas = 1.0 - betas
        alphas_cumprod = np.cumprod(alphas, axis=0)
        alphas_cumprod_prev = np.append(1.0, alphas_cumprod[:-1])

        self.betas = tf.constant(betas, dtype=tf.float32)
        self.alphas_cumprod = tf.constant(alphas_cumprod, dtype=tf.float32)
        self.alphas_cumprod_prev = tf.constant(alphas_cumprod_prev, dtype=tf.float32)

        # Calculations for diffusion q(x_t | x_{t-1}) and others
        self.sqrt_alphas_cumprod = tf.constant(
            np.sqrt(alphas_cumprod), dtype=tf.float32
        )

        self.sqrt_one_minus_alphas_cumprod = tf.constant(
            np.sqrt(1.0 - alphas_cumprod), dtype=tf.float32
        )

        self.log_one_minus_alphas_cumprod = tf.constant(
            np.log(1.0 - alphas_cumprod), dtype=tf.float32
        )

        self.sqrt_recip_alphas_cumprod = tf.constant(
            np.sqrt(1.0 / alphas_cumprod), dtype=tf.float32
        )
        self.sqrt_recipm1_alphas_cumprod = tf.constant(
            np.sqrt(1.0 / alphas_cumprod - 1), dtype=tf.float32
        )

        # Calculations for posterior q(x_{t-1} | x_t, x_0)
        posterior_variance = (
            betas * (1.0 - alphas_cumprod_prev) / (1.0 - alphas_cumprod)
        )
        self.posterior_variance = tf.constant(posterior_variance, dtype=tf.float32)
```

```
        # Log calculation clipped because the posterior variance is 0 at the beginning
        # of the diffusion chain
        self.posterior_log_variance_clipped = tf.constant(
            np.log(np.maximum(posterior_variance, 1e-20)), dtype=tf.float32
        )

        self.posterior_mean_coef1 = tf.constant(
            betas * np.sqrt(alphas_cumprod_prev) / (1.0 - alphas_cumprod),
            dtype=tf.float32,
        )

        self.posterior_mean_coef2 = tf.constant(
            (1.0 - alphas_cumprod_prev) * np.sqrt(alphas) / (1.0 - alphas_cumprod),
            dtype=tf.float32,
        )

    def _extract(self, a, t, x_shape):
        """Extract some coefficients at specified timesteps,
        then reshape to [batch_size, 1, 1, 1, 1, ...] for broadcasting purposes.

        Args:
            a: Tensor to extract from
            t: Timestep for which the coefficients are to be extracted
            x_shape: Shape of the current batched samples
        """
        batch_size = x_shape[0]
        out = tf.gather(a, t)
        return tf.reshape(out, [batch_size, 1, 1, 1])

    def q_mean_variance(self, x_start, t):
        """Extracts the mean, and the variance at current timestep.

        Args:
            x_start: Initial sample (before the first diffusion step)
            t: Current timestep
        """
        x_start_shape = tf.shape(x_start)
        mean = self._extract(self.sqrt_alphas_cumprod, t, x_start_shape) * x_start
        variance = self._extract(1.0 - self.alphas_cumprod, t, x_start_shape)
        log_variance = self._extract(
            self.log_one_minus_alphas_cumprod, t, x_start_shape
        )
        return mean, variance, log_variance

    def q_sample(self, x_start, t, noise):
        """Diffuse the data.

        Args:
            x_start: Initial sample (before the first diffusion step)
            t: Current timestep
            noise: Gaussian noise to be added at the current timestep
        Returns:
            Diffused samples at timestep `t`
        """
        x_start_shape = tf.shape(x_start)
        return (
            self._extract(self.sqrt_alphas_cumprod, t, tf.shape(x_start)) * x_start
            + self._extract(self.sqrt_one_minus_alphas_cumprod, t, x_start_shape)
            * noise
        )

    def predict_start_from_noise(self, x_t, t, noise):
```

```
        x_t_shape = tf.shape(x_t)
        return (
            self._extract(self.sqrt_recip_alphas_cumprod, t, x_t_shape) * x_t
            - self._extract(self.sqrt_recipm1_alphas_cumprod, t, x_t_shape) * noise
        )

    def q_posterior(self, x_start, x_t, t):
        """Compute the mean and variance of the diffusion
        posterior q(x_{t-1} | x_t, x_0).

        Args:
            x_start: Stating point(sample) for the posterior computation
            x_t: Sample at timestep `t`
            t: Current timestep
        Returns:
            Posterior mean and variance at current timestep
        """

        x_t_shape = tf.shape(x_t)
        posterior_mean = (
            self._extract(self.posterior_mean_coef1, t, x_t_shape) * x_start
            + self._extract(self.posterior_mean_coef2, t, x_t_shape) * x_t
        )
        posterior_variance = self._extract(self.posterior_variance, t, x_t_shape)
        posterior_log_variance_clipped = self._extract(
            self.posterior_log_variance_clipped, t, x_t_shape
        )
        return posterior_mean, posterior_variance, posterior_log_variance_clipped

    def p_mean_variance(self, pred_noise, x, t, clip_denoised=True):
        x_recon = self.predict_start_from_noise(x, t=t, noise=pred_noise)
        if clip_denoised:
            x_recon = tf.clip_by_value(x_recon, self.clip_min, self.clip_max)

        model_mean, posterior_variance, posterior_log_variance = self.q_posterior(
            x_start=x_recon, x_t=x, t=t
        )
        return model_mean, posterior_variance, posterior_log_variance

    def p_sample(self, pred_noise, x, t, clip_denoised=True):
        """Sample from the diffusion model.

        Args:
            pred_noise: Noise predicted by the diffusion model
            x: Samples at a given timestep for which the noise was predicted
            t: Current timestep
            clip_denoised (bool): Whether to clip the predicted noise
                within the specified range or not.
        """
        model_mean, _, model_log_variance = self.p_mean_variance(
            pred_noise, x=x, t=t, clip_denoised=clip_denoised
        )
        noise = tf.random.normal(shape=x.shape, dtype=x.dtype)
        # No noise when t == 0
        nonzero_mask = tf.reshape(
            1 - tf.cast(tf.equal(t, 0), tf.float32), [tf.shape(x)[0], 1, 1, 1]
        )
        return model_mean + nonzero_mask * tf.exp(0.5 * model_log_variance) * noise
```

Network architecture

U-Net, originally developed for semantic segmentation, is an architecture that is widely used for implementing diffusion models but with some slight modifications:

1. The network accepts two inputs: Image and time step
2. Self-attention between the convolution blocks once we reach a specific resolution (16x16 in the paper)
3. Group Normalization instead of weight normalization

We implement most of the things as used in the original paper. We use the `swish` activation function throughout the network. We use the variance scaling kernel initializer.

The only difference here is the number of groups used for the `GroupNormalization` layer. For the flowers dataset, we found that a value of `groups=8` produces better results compared to the default value of `groups=32`. Dropout is optional and should be used where chances of over fitting is high. In the paper, the authors used dropout only when training on CIFAR10.

In [ ]:

```
# Kernel initializer to use
def kernel_init(scale):
    scale = max(scale, 1e-10)
    return keras.initializers.VarianceScaling(
        scale, mode="fan_avg", distribution="uniform"
    )


class AttentionBlock(layers.Layer):
    """Applies self-attention.

    Args:
        units: Number of units in the dense layers
        groups: Number of groups to be used for GroupNormalization layer
    """

    def __init__(self, units, groups=8, **kwargs):
        self.units = units
        self.groups = groups
        super().__init__(**kwargs)

        self.norm = tfa.layers.GroupNormalization(groups=groups)
        self.query = layers.Dense(units, kernel_initializer=kernel_init(1.0))
        self.key = layers.Dense(units, kernel_initializer=kernel_init(1.0))
        self.value = layers.Dense(units, kernel_initializer=kernel_init(1.0))
        self.proj = layers.Dense(units, kernel_initializer=kernel_init(0.0))

    def call(self, inputs):
        batch_size = tf.shape(inputs)[0]
        height = tf.shape(inputs)[1]
        width = tf.shape(inputs)[2]
        scale = tf.cast(self.units, tf.float32) ** (-0.5)

        inputs = self.norm(inputs)
        q = self.query(inputs)
        k = self.key(inputs)
        v = self.value(inputs)

        attn_score = tf.einsum("bhwc, bHWc->bhwHW", q, k) * scale
        attn_score = tf.reshape(attn_score, [batch_size, height, width, height * width]

        attn_score = tf.nn.softmax(attn_score, -1)
```

```python
        attn_score = tf.reshape(attn_score, [batch_size, height, width, height, width])

        proj = tf.einsum("bhwHW,bHWc->bhwc", attn_score, v)
        proj = self.proj(proj)
        return inputs + proj


class TimeEmbedding(layers.Layer):
    def __init__(self, dim, **kwargs):
        super().__init__(**kwargs)
        self.dim = dim
        self.half_dim = dim // 2
        self.emb = math.log(10000) / (self.half_dim - 1)
        self.emb = tf.exp(tf.range(self.half_dim, dtype=tf.float32) * -self.emb)

    def call(self, inputs):
        inputs = tf.cast(inputs, dtype=tf.float32)
        emb = inputs[:, None] * self.emb[None, :]
        emb = tf.concat([tf.sin(emb), tf.cos(emb)], axis=-1)
        return emb


def ResidualBlock(width, groups=8, activation_fn=keras.activations.swish):
    def apply(inputs):
        x, t = inputs
        input_width = x.shape[3]

        if input_width == width:
            residual = x
        else:
            residual = layers.Conv2D(
                width, kernel_size=1, kernel_initializer=kernel_init(1.0)
            )(x)

        temb = activation_fn(t)
        temb = layers.Dense(width, kernel_initializer=kernel_init(1.0))(temb)[
            :, None, None, :
        ]

        x = tfa.layers.GroupNormalization(groups=groups)(x)
        x = activation_fn(x)
        x = layers.Conv2D(
            width, kernel_size=3, padding="same", kernel_initializer=kernel_init(1.0)
        )(x)

        x = layers.Add()([x, temb])
        x = tfa.layers.GroupNormalization(groups=groups)(x)
        x = activation_fn(x)

        x = layers.Conv2D(
            width, kernel_size=3, padding="same", kernel_initializer=kernel_init(0.0)
        )(x)
        x = layers.Add()([x, residual])
        return x

    return apply


def DownSample(width):
    def apply(x):
        x = layers.Conv2D(
            width,
            kernel_size=3,
```

```
            strides=2,
            padding="same",
            kernel_initializer=kernel_init(1.0),
        )(x)
        return x

    return apply


def UpSample(width, interpolation="nearest"):
    def apply(x):
        x = layers.UpSampling2D(size=2, interpolation=interpolation)(x)
        x = layers.Conv2D(
            width, kernel_size=3, padding="same", kernel_initializer=kernel_init(1.0)
        )(x)
        return x

    return apply


def TimeMLP(units, activation_fn=keras.activations.swish):
    def apply(inputs):
        temb = layers.Dense(
            units, activation=activation_fn, kernel_initializer=kernel_init(1.0)
        )(inputs)
        temb = layers.Dense(units, kernel_initializer=kernel_init(1.0))(temb)
        return temb

    return apply


def build_model(
    img_size,
    img_channels,
    widths,
    has_attention,
    num_res_blocks=2,
    norm_groups=8,
    interpolation="nearest",
    activation_fn=keras.activations.swish,
):
    image_input = layers.Input(
        shape=(img_size, img_size, img_channels), name="image_input"
    )
    time_input = keras.Input(shape=(), dtype=tf.int64, name="time_input")

    x = layers.Conv2D(
        first_conv_channels,
        kernel_size=(3, 3),
        padding="same",
        kernel_initializer=kernel_init(1.0),
    )(image_input)

    temb = TimeEmbedding(dim=first_conv_channels * 4)(time_input)
    temb = TimeMLP(units=first_conv_channels * 4, activation_fn=activation_fn)(temb)

    skips = [x]

    # DownBlock
    for i in range(len(widths)):
        for _ in range(num_res_blocks):
            x = ResidualBlock(
                widths[i], groups=norm_groups, activation_fn=activation_fn
```

```
            )([x, temb])
            if has_attention[i]:
                x = AttentionBlock(widths[i], groups=norm_groups)(x)
            skips.append(x)

        if widths[i] != widths[-1]:
            x = DownSample(widths[i])(x)
            skips.append(x)

    # MiddleBlock
    x = ResidualBlock(widths[-1], groups=norm_groups, activation_fn=activation_fn)(
        [x, temb]
    )
    x = AttentionBlock(widths[-1], groups=norm_groups)(x)
    x = ResidualBlock(widths[-1], groups=norm_groups, activation_fn=activation_fn)(
        [x, temb]
    )

    # UpBlock
    for i in reversed(range(len(widths))):
        for _ in range(num_res_blocks + 1):
            x = layers.Concatenate(axis=-1)([x, skips.pop()])
            x = ResidualBlock(
                widths[i], groups=norm_groups, activation_fn=activation_fn
            )([x, temb])
            if has_attention[i]:
                x = AttentionBlock(widths[i], groups=norm_groups)(x)

        if i != 0:
            x = UpSample(widths[i], interpolation=interpolation)(x)

    # End block
    x = tfa.layers.GroupNormalization(groups=norm_groups)(x)
    x = activation_fn(x)
    x = layers.Conv2D(3, (3, 3), padding="same", kernel_initializer=kernel_init(0.0))(x
    return keras.Model([image_input, time_input], x, name="unet")
```

Training

We follow the same setup for training the diffusion model as described in the paper. We use `Adam` optimizer with a learning rate of `2e-4`. We use EMA on model parameters with a decay factor of 0.999. We treat our model as noise prediction network i.e. at every training step, we input a batch of images and corresponding time steps to our UNet, and the network outputs the noise as predictions.

The only difference is that we aren't using the Kernel Inception Distance (KID) or Frechet Inception Distance (FID) for evaluating the quality of generated samples during training. This is because both these metrics are compute heavy and are skipped for the brevity of implementation.

Note: We are using mean squared error as the loss function which is aligned with the paper, and theoretically makes sense. In practice, though, it is also common to use mean absolute error or Huber loss as the loss function.

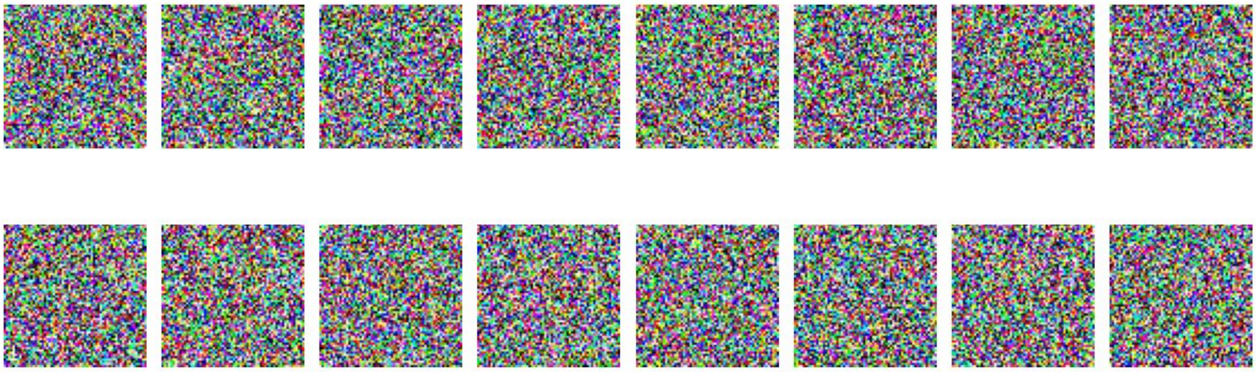
In [ ]:

```
class DiffusionModel(keras.Model):
    def __init__(self, network, ema_network, timesteps, gdf_util, ema=0.999):
        super().__init__()
        self.network = network
```

```
        self.ema_network = ema_network
        self.timesteps = timesteps
        self.gdf_util = gdf_util
        self.ema = ema

    def train_step(self, images):
        # 1. Get the batch size
        batch_size = tf.shape(images)[0]

        # 2. Sample timesteps uniformly
        t = tf.random.uniform(
            minval=0, maxval=self.timesteps, shape=(batch_size,), dtype=tf.int64
        )

        with tf.GradientTape() as tape:
            # 3. Sample random noise to be added to the images in the batch
            noise = tf.random.normal(shape=tf.shape(images), dtype=images.dtype)

            # 4. Diffuse the images with noise
            images_t = self.gdf_util.q_sample(images, t, noise)

            # 5. Pass the diffused images and time steps to the network
            pred_noise = self.network([images_t, t], training=True)

            # 6. Calculate the loss
            loss = self.loss(noise, pred_noise)

        # 7. Get the gradients
        gradients = tape.gradient(loss, self.network.trainable_weights)

        # 8. Update the weights of the network
        self.optimizer.apply_gradients(zip(gradients, self.network.trainable_weights))

        # 9. Updates the weight values for the network with EMA weights
        for weight, ema_weight in zip(self.network.weights, self.ema_network.weights):
            ema_weight.assign(self.ema * ema_weight + (1 - self.ema) * weight)

        # 10. Return loss values
        return {"loss": loss}

    def generate_images(self, num_images=16):
        # 1. Randomly sample noise (starting point for reverse process)
        samples = tf.random.normal(
            shape=(num_images, img_size, img_size, img_channels), dtype=tf.float32
        )
        # 2. Sample from the model iteratively
        for t in reversed(range(0, self.timesteps)):
            tt = tf.cast(tf.fill(num_images, t), dtype=tf.int64)
            pred_noise = self.ema_network.predict(
                [samples, tt], verbose=0, batch_size=num_images
            )
            samples = self.gdf_util.p_sample(
                pred_noise, samples, tt, clip_denoised=True
            )
        # 3. Return generated samples
        return samples

    def plot_images(
        self, epoch=None, logs=None, num_rows=2, num_cols=8, figsize=(12, 5)
    ):
        """Utility to plot images using the diffusion model during training."""
        generated_samples = self.generate_images(num_images=num_rows * num_cols)
        generated_samples = (
```

```
            tf.clip_by_value(generated_samples * 127.5 + 127.5, 0.0, 255.0)
            .numpy()
            .astype(np.uint8)
        )

        _, ax = plt.subplots(num_rows, num_cols, figsize=figsize)
        for i, image in enumerate(generated_samples):
            if num_rows == 1:
                ax[i].imshow(image)
                ax[i].axis("off")
            else:
                ax[i // num_cols, i % num_cols].imshow(image)
                ax[i // num_cols, i % num_cols].axis("off")

        plt.tight_layout()
        plt.show()


# Build the unet model
network = build_model(
    img_size=img_size,
    img_channels=img_channels,
    widths=widths,
    has_attention=has_attention,
    num_res_blocks=num_res_blocks,
    norm_groups=norm_groups,
    activation_fn=keras.activations.swish,
)
ema_network = build_model(
    img_size=img_size,
    img_channels=img_channels,
    widths=widths,
    has_attention=has_attention,
    num_res_blocks=num_res_blocks,
    norm_groups=norm_groups,
    activation_fn=keras.activations.swish,
)
ema_network.set_weights(network.get_weights())  # Initially the weights are the same

# Get an instance of the Gaussian Diffusion utilities
gdf_util = GaussianDiffusion(timesteps=total_timesteps)

# Get the model
model = DiffusionModel(
    network=network,
    ema_network=ema_network,
    gdf_util=gdf_util,
    timesteps=total_timesteps,
)

# Compile the model
model.compile(
    loss=keras.losses.MeanSquaredError(),
    optimizer=keras.optimizers.Adam(learning_rate=learning_rate),
)

# Train the model
model.fit(
    train_ds,
    epochs=num_epochs,
    batch_size=batch_size,
    callbacks=[keras.callbacks.LambdaCallback(on_epoch_end=model.plot_images)],
)
```

```
31/31 [==============================] - ETA: 0s - loss: 0.7773
```



```
31/31 [==============================] - 347s 8s/step - loss: 0.7690
```

Out[ ]:

```
<keras.src.callbacks.History at 0x781d5ff34190>
```

Results

We trained this model for 800 epochs on a V100 GPU, and each epoch took almost 8 seconds to finish. We load those weights here, and we generate a few samples starting from pure noise.

In [ ]:

```
!curl -LO https://github.com/AakashKumarNain/ddpms/releases/download/v3.0.0/checkpoints
!unzip -qq checkpoints.zip
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100  222M  100  222M    0     0  47.1M      0  0:00:04  0:00:04 --:--:-- 56.1M
```

In [ ]:

```
# Load the model weights
model.ema_network.load_weights("checkpoints/diffusion_model_checkpoint")

# Generate and plot some samples
model.plot_images(num_rows=4, num_cols=8)
```

References

You can find the original introduction by A_K_Nain here.

1. Denoising Diffusion Probabilistic Models
2. Author's implementation
3. A deep dive into DDPMs
4. Denoising Diffusion Implicit Models
5. Annotated Diffusion Model
6. AIAIART

Assignment

In this assignment, you have to implement the DDPMs with the CelebA dataset.

Description of Dataset

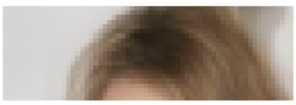
1. The raw data is from Large-scale CelebFaces Attributes (CelebA) Dataset, please download it
    - TensorFlow Datasets has also provide CelebA, but we suggust you to download it and use it locally
2. CelebA has 202,599 number of face images

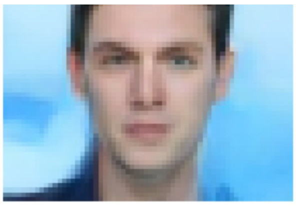
The sample images are shown below:

sample images

Requirements

- Use the CelebA dataset to train DDPMs and use the trained model to plot your results in (num_rows=4, num_cols=8), just like what has been done in the example code
- Briefly summarize what you did and explain the performance results (loss and time consuming)
- This assignment does not specify a clear model loss threshold. However, please train your model to the extent that it can generate images with clearly recognizable human faces. For example:

sample results