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COLLEGE OF ENGINEERING AND ARCHITECTURE
ELECTRONICS ENGINEERING DEPARTMENT

COE 005 – Prediction and Machine Learning
ECE41S11

Generative Adversarial Network

Class Exercise
Using styleGAN for Image Generation

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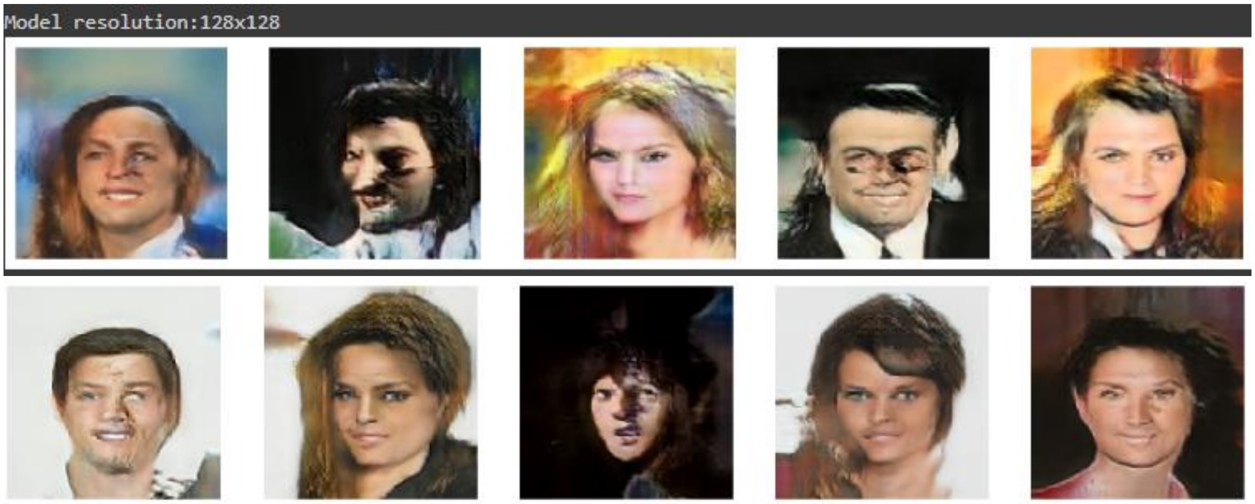
Dataset

Celeb_A dataset items

Sample outputs



In this activity, a demonstration of face image generation using GAN was conducted. Generative Adversarial Networks is a network for generating data from scratch using 2 different NN models that compete with each other. These 2 networks are knowns the generator and discriminator. The generator is a convolutional NN that creates numerous images with the goal of fooling the discriminator. As the name suggests, the discriminator is a deconvolutional NN that is in charge of detecting if the image generated by the generator is real and fake, and whenever there's an outcome, it is used to feed back to the generator to train itself in fooling the discriminator better. In this activity, styleGAN is used.

The following are the machine learning code used to perform styleGAN with Google Colab as the compiler.

Initial part of the code is to call the general libraries and to mount Gdrive to get the directory for the dataset and to perform the different functions later on related to DCGAN.

```
[6] import os
    import random
    import math
    import numpy as np
    import matplotlib.pyplot as plt

    from enum import Enum
    from glob import glob
    from functools import partial

    import tensorflow as tf
    from tensorflow import keras
    from tensorflow.keras import layers
    from tensorflow.keras.models import Sequential
    from tensorflow_addons.layers import InstanceNormalization

    import gdown
    from zipfile import ZipFile
```

Next, the source images were also imported. The images were resized to 64x64. As seen, the dataset contains 202599 files of different celebrity face images and angles. A function for assigning a batch size depending on resolution is applied, this influences the training step later on.

```
[7] def log2(x):
        return int(np.log2(x))


    # we use different batch size for different resolution, so larger image size
    # could fit into GPU memory. The keys is image resolution in log2
    batch_sizes = {2: 16, 3: 16, 4: 16, 5: 16, 6: 16, 7: 8, 8: 4, 9: 2, 10: 1}
    # We adjust the train step accordingly
    train_step_ratio = {k: batch_sizes[2] / v for k, v in batch_sizes.items()}


    os.makedirs("celeba_gan")

    url = "https://drive.google.com/uc?id=1O7m1010EJjLE5QxLZiM9Fpjs7Oj6e684"
    output = "celeba_gan/data.zip"
    gdown.download(url, output, quiet=True)

    with ZipFile("celeba_gan/data.zip", "r") as zipobj:
        zipobj.extractall("celeba_gan")

    # Create a dataset from our folder, and rescale the images to the [0-1] range:

    ds_train = keras.preprocessing.image_dataset_from_directory(
        "celeba_gan", label_mode=None, image_size=(64, 64), batch_size=32
    )
    ds_train = ds_train.map(lambda x: x / 255.0)


    def resize_image(res, image):
        # only donwsampling, so use nearest neighbor that is faster to run
        image = tf.image.resize(
            image, (res, res), method=tf.image.ResizeMethod.NEAREST_NEIGHBOR
        )
        image = tf.cast(image, tf.float32) / 127.5 - 1.0
        return image


    def create_dataloader(res):
        batch_size = batch_sizes[log2(res)]
        # NOTE: we unbatch the dataset so we can `batch()` it again with the `drop_remainder=True` option
        # since the model only supports a single batch size
        dl = ds_train.map(partial(resize_image, res), num_parallel_calls=tf.data.AUTOTUNE).unbatch()
        dl = dl.shuffle(200).batch(batch_size, drop_remainder=True).prefetch(1).repeat()
        return dl

    Found 202599 files belonging to 1 classes.
```

A function for displaying the images after every epoch is defined.

```
[8] def plot_images(images, log2_res, fname=""):
        scales = {2: 0.5, 3: 1, 4: 2, 5: 3, 6: 4, 7: 5, 8: 6, 9: 7, 10: 8}
        scale = scales[log2_res]

        grid_col = min(images.shape[0], int(32 // scale))
        grid_row = 1

        f, axarr = plt.subplots(
            grid_row, grid_col, figsize=(grid_col * scale, grid_row * scale)
        )

        for row in range(grid_row):
            ax = axarr if grid_row == 1 else axarr[row]
            for col in range(grid_col):
                ax[col].imshow(images[row * grid_col + col])
                ax[col].axis("off")
        plt.show()
        if fname:
            f.savefig(fname)
```

Functions were defined for the different parameters used for building the generator and discriminator.

```
[9] def fade_in(alpha, a, b):
        return alpha * a + (1.0 - alpha) * b


    def wasserstein_loss(y_true, y_pred):
        return -tf.reduce_mean(y_true * y_pred)


    def pixel_norm(x, epsilon=1e-8):
        return x / tf.math.sqrt(tf.reduce_mean(x ** 2, axis=-1, keepdims=True) + epsilon)


    def minibatch_std(input_tensor, epsilon=1e-8):
        n, h, w, c = tf.shape(input_tensor)
        group_size = tf.minimum(4, n)
        x = tf.reshape(input_tensor, [group_size, -1, h, w, c])
        group_mean, group_var = tf.nn.moments(x, axes=(0), keepdims=False)
        group_std = tf.sqrt(group_var + epsilon)
        avg_std = tf.reduce_mean(group_std, axis=[1, 2, 3], keepdims=True)
        x = tf.tile(avg_std, [group_size, h, w, 1])
        return tf.concat([input_tensor, x], axis=-1)


    class EqualizedConv(layers.Layer):
        def __init__(self, out_channels, kernel=3, gain=2, **kwargs):
            super(EqualizedConv, self).__init__(**kwargs)
            self.kernel = kernel
            self.out_channels = out_channels
            self.gain = gain
            self.pad = kernel != 1

        def build(self, input_shape):
            self.in_channels = input_shape[-1]
            initializer = keras.initializers.RandomNormal(mean=0.0, stddev=1.0)
            self.w = self.add_weight(
                shape=[self.kernel, self.kernel, self.in_channels, self.out_channels],
                initializer=initializer,
                trainable=True,
                name="kernel",
            )
            self.b = self.add_weight(
                shape=(self.out_channels,), initializer="zeros", trainable=True, name="bias"
            )
            fan_in = self.kernel * self.kernel * self.in_channels
            self.scale = tf.sqrt(self.gain / fan_in)

        def call(self, inputs):
            if self.pad:
                x = tf.pad(inputs, [[0, 0], [1, 1], [1, 1], [0, 0]], mode="REFLECT")
            else:
                x = inputs
            output = (
                tf.nn.conv2d(x, self.scale * self.w, strides=1, padding="VALID") + self.b
            )
            return output
```

```
class EqualizedDense(layers.Layer):
    def __init__(self, units, gain=2, learning_rate_multiplier=1, **kwargs):
        super(EqualizedDense, self).__init__(**kwargs)
        self.units = units
        self.gain = gain
        self.learning_rate_multiplier = learning_rate_multiplier

    def build(self, input_shape):
        self.in_channels = input_shape[-1]
        initializer = keras.initializers.RandomNormal(
            mean=0.0, stddev=1.0 / self.learning_rate_multiplier
        )
        self.w = self.add_weight(
            shape=[self.in_channels, self.units],
            initializer=initializer,
            trainable=True,
            name="kernel",
        )
        self.b = self.add_weight(
            shape=(self.units,), initializer="zeros", trainable=True, name="bias"
        )
        fan_in = self.in_channels
        self.scale = tf.sqrt(self.gain / fan_in)

    def call(self, inputs):
        output = tf.add(tf.matmul(inputs, self.scale * self.w), self.b)
        return output * self.learning_rate_multiplier


class AddNoise(layers.Layer):
    def build(self, input_shape):
        n, h, w, c = input_shape[0]
        initializer = keras.initializers.RandomNormal(mean=0.0, stddev=1.0)
        self.b = self.add_weight(
            shape=[1, 1, 1, c], initializer=initializer, trainable=True, name="kernel"
        )

    def call(self, inputs):
        x, noise = inputs
        output = x + self.b * noise
        return output


class AdaIN(layers.Layer):
    def __init__(self, gain=1, **kwargs):
        super(AdaIN, self).__init__(**kwargs)
        self.gain = gain

    def build(self, input_shapes):
        x_shape = input_shapes[0]
        w_shape = input_shapes[1]

        self.w_channels = w_shape[-1]
        self.x_channels = x_shape[-1]

        self.dense_1 = EqualizedDense(self.x_channels, gain=1)
        self.dense_2 = EqualizedDense(self.x_channels, gain=1)

    def call(self, inputs):
        x, w = inputs
        ys = tf.reshape(self.dense_1(w), (-1, 1, 1, self.x_channels))
        yb = tf.reshape(self.dense_2(w), (-1, 1, 1, self.x_channels))
        return ys * x + yb
```

A function for mapping the random noise into the style code is defined.

```
[10] def Mapping(num_stages, input_shape=512):
         z = layers.Input(shape=(input_shape))
         w = pixel_norm(z)
         for i in range(8):
             w = EqualizedDense(512, learning_rate_multiplier=0.01)(w)
             w = layers.LeakyReLU(0.2)(w)
         w = tf.tile(tf.expand_dims(w, 1), (1, num_stages, 1))
         return keras.Model(z, w, name="mapping")
```

Next, the generator network is defined. This will act as the creator of the real/image which will undergo classifying by the discriminator

```python
class Generator:
    def __init__(self, start_res_log2, target_res_log2):
        self.start_res_log2 = start_res_log2
        self.target_res_log2 = target_res_log2
        self.num_stages = target_res_log2 - start_res_log2 + 1
        # list of generator blocks at increasing resolution
        self.g_blocks = []
        # list of layers to convert g_block activation to RGB
        self.to_rgb = []
        # list of noise input of different resolutions into g_blocks
        self.noise_inputs = []
        # filter size to use at each stage, keys are log2(resolution)
        self.filter_nums = {
            0: 512,
            1: 512,
            2: 512,  # 4x4
            3: 512,  # 8x8
            4: 512,  # 16x16
            5: 512,  # 32x32
            6: 256,  # 64x64
            7: 128,  # 128x128
            8: 64,  # 256x256
            9: 32,  # 512x512
            10: 16,
        }  # 1024x1024

        start_res = 2 ** start_res_log2
        self.input_shape = (start_res, start_res, self.filter_nums[start_res_log2])
        self.g_input = layers.Input(self.input_shape, name="generator_input")

        for i in range(start_res_log2, target_res_log2 + 1):
            filter_num = self.filter_nums[i]
            res = 2 ** i
            self.noise_inputs.append(
                layers.Input(shape=(res, res, 1), name=f"noise_{res}x{res}")
            )
            to_rgb = Sequential(
                [
                    layers.InputLayer(input_shape=(res, res, filter_num)),
                    EqualizedConv(3, 1, gain=1),
                ],
                name=f"to_rgb_{res}x{res}",
            )
            self.to_rgb.append(to_rgb)
            is_base = i == self.start_res_log2
            if is_base:
                input_shape = (res, res, self.filter_nums[i - 1])
            else:
                input_shape = (2 ** (i - 1), 2 ** (i - 1), self.filter_nums[i - 1])
            g_block = self.build_block(
                filter_num, res=res, input_shape=input_shape, is_base=is_base
            )
            self.g_blocks.append(g_block)
```

```python
def build_block(self, filter_num, res, input_shape, is_base):
    input_tensor = layers.Input(shape=input_shape, name=f"g_{res}")
    noise = layers.Input(shape=(res, res, 1), name=f"noise_{res}")
    w = layers.Input(shape=512)
    x = input_tensor

    if not is_base:
        x = layers.UpSampling2D((2, 2))(x)
        x = EqualizedConv(filter_num, 3)(x)

    x = AddNoise()([x, noise])
    x = layers.LeakyReLU(0.2)(x)
    x = InstanceNormalization()(x)
    x = AdaIN()([x, w])

    x = EqualizedConv(filter_num, 3)(x)
    x = AddNoise()([x, noise])
    x = layers.LeakyReLU(0.2)(x)
    x = InstanceNormalization()(x)
    x = AdaIN()([x, w])
    return keras.Model([input_tensor, w, noise], x, name=f"genblock_{res}x{res}")

def grow(self, res_log2):
    res = 2 ** res_log2

    num_stages = res_log2 - self.start_res_log2 + 1
    w = layers.Input(shape=(self.num_stages, 512), name="w")

    alpha = layers.Input(shape=(1), name="g_alpha")
    x = self.g_blocks[0]([self.g_input, w[:, 0], self.noise_inputs[0]])

    if num_stages == 1:
        rgb = self.to_rgb[0](x)
    else:
        for i in range(1, num_stages - 1):

            x = self.g_blocks[i]([x, w[:, i], self.noise_inputs[i]])

        old_rgb = self.to_rgb[num_stages - 2](x)
        old_rgb = layers.UpSampling2D((2, 2))(old_rgb)

        i = num_stages - 1
        x = self.g_blocks[i]([x, w[:, i], self.noise_inputs[i]])

        new_rgb = self.to_rgb[i](x)

        rgb = fade_in(alpha[0], new_rgb, old_rgb)

    return keras.Model(
        [self.g_input, w, self.noise_inputs, alpha],
        rgb,
        name=f"generator_{res}_x_{res}",
    )
```

The Discriminator model was also defined incorporating the parameters defined earlier.

```python
[10]
    class Discriminator:
        def __init__(self, start_res_log2, target_res_log2):
            self.start_res_log2 = start_res_log2
            self.target_res_log2 = target_res_log2
            self.num_stages = target_res_log2 - start_res_log2 + 1
            # filter size to use at each stage, keys are log2(resolution)
            self.filter_nums = {
                0: 512,
                1: 512,
                2: 512,  # 4x4
                3: 512,  # 8x8
                4: 512,  # 16x16
                5: 512,  # 32x32
                6: 256,  # 64x64
                7: 128,  # 128x128
                8: 64,  # 256x256
                9: 32,  # 512x512
                10: 16,
            }  # 1024x1024
            # list of discriminator blocks at increasing resolution
            self.d_blocks = []
            # list of layers to convert RGB into activation for d_blocks inputs
            self.from_rgb = []

            for res_log2 in range(self.start_res_log2, self.target_res_log2 + 1):
                res = 2 ** res_log2
                filter_num = self.filter_nums[res_log2]
                from_rgb = Sequential(
                    [
                        layers.InputLayer(
                            input_shape=(res, res, 3), name=f"from_rgb_input_{res}"
                        ),
                        EqualizedConv(filter_num, 1),
                        layers.LeakyReLU(0.2),
                    ],
                    name=f"from_rgb_{res}",
                )

                self.from_rgb.append(from_rgb)

                input_shape = (res, res, filter_num)
                if len(self.d_blocks) == 0:
                    d_block = self.build_base(filter_num, res)
                else:
                    d_block = self.build_block(
                        filter_num, self.filter_nums[res_log2 - 1], res
                    )

                self.d_blocks.append(d_block)
```

```python
def build_base(self, filter_num, res):
    input_tensor = layers.Input(shape=(res, res, filter_num), name=f"d_{res}")
    x = minibatch_std(input_tensor)
    x = EqualizedConv(filter_num, 3)(x)
    x = layers.LeakyReLU(0.2)(x)
    x = layers.Flatten()(x)
    x = EqualizedDense(filter_num)(x)
    x = layers.LeakyReLU(0.2)(x)
    x = EqualizedDense(1)(x)
    return keras.Model(input_tensor, x, name=f"d_{res}")

def build_block(self, filter_num_1, filter_num_2, res):
    input_tensor = layers.Input(shape=(res, res, filter_num_1), name=f"d_{res}")
    x = EqualizedConv(filter_num_1, 3)(input_tensor)
    x = layers.LeakyReLU(0.2)(x)
    x = EqualizedConv(filter_num_2)(x)
    x = layers.LeakyReLU(0.2)(x)
    x = layers.AveragePooling2D((2, 2))(x)
    return keras.Model(input_tensor, x, name=f"d_{res}")

def grow(self, res_log2):
    res = 2 ** res_log2
    idx = res_log2 - self.start_res_log2
    alpha = layers.Input(shape=(1), name="d_alpha")
    input_image = layers.Input(shape=(res, res, 3), name="input_image")
    x = self.from_rgb[idx](input_image)
    x = self.d_blocks[idx](x)
    if idx > 0:
        idx -= 1
        downsized_image = layers.AveragePooling2D((2, 2))(input_image)
        y = self.from_rgb[idx](downsized_image)
        x = fade_in(alpha[0], x, y)

        for i in range(idx, -1, -1):
            x = self.d_blocks[i](x)
    return keras.Model([input_image, alpha], x, name=f"discriminator_{res}_x_{res}")
```

The StyleGAN model with custom train_step metrics. Metrics to be used were also defined to gauge the progress of the model throughout the training epochs.

```python
class StyleGAN(tf.keras.Model):
    def __init__(self, z_dim=512, target_res=64, start_res=4):
        super(StyleGAN, self).__init__()
        self.z_dim = z_dim

        self.target_res_log2 = log2(target_res)
        self.start_res_log2 = log2(start_res)
        self.current_res_log2 = self.target_res_log2
        self.num_stages = self.target_res_log2 - self.start_res_log2 + 1

        self.alpha = tf.Variable(1.0, dtype=tf.float32, trainable=False, name="alpha")

        self.mapping = Mapping(num_stages=self.num_stages)
        self.d_builder = Discriminator(self.start_res_log2, self.target_res_log2)
        self.g_builder = Generator(self.start_res_log2, self.target_res_log2)
        self.g_input_shape = self.g_builder.input_shape

        self.phase = None
        self.train_step_counter = tf.Variable(0, dtype=tf.int32, trainable=False)

        self.loss_weights = {"gradient_penalty": 10, "drift": 0.001}

    def grow_model(self, res):
        tf.keras.backend.clear_session()
        res_log2 = log2(res)
        self.generator = self.g_builder.grow(res_log2)
        self.discriminator = self.d_builder.grow(res_log2)
        self.current_res_log2 = res_log2
        print(f"\nModel resolution:{res}x{res}")

    def compile(
        self, steps_per_epoch, phase, res, d_optimizer, g_optimizer, *args, **kwargs
    ):
        self.loss_weights = kwargs.pop("loss_weights", self.loss_weights)
        self.steps_per_epoch = steps_per_epoch
        if res != 2 ** self.current_res_log2:
            self.grow_model(res)
            self.d_optimizer = d_optimizer
            self.g_optimizer = g_optimizer

        self.train_step_counter.assign(0)
        self.phase = phase
        self.d_loss_metric = keras.metrics.Mean(name="d_loss")
        self.g_loss_metric = keras.metrics.Mean(name="g_loss")
        super(StyleGAN, self).compile(*args, **kwargs)

    @property
    def metrics(self):
        return [self.d_loss_metric, self.g_loss_metric]

    def generate_noise(self, batch_size):
        noise = [
            tf.random.normal((batch_size, 2 ** res, 2 ** res, 1))
            for res in range(self.start_res_log2, self.target_res_log2 + 1)
        ]
        return noise

    def gradient_loss(self, grad):
        loss = tf.square(grad)
        loss = tf.reduce_sum(loss, axis=tf.range(1, tf.size(tf.shape(loss))))
        loss = tf.sqrt(loss)
        loss = tf.reduce_mean(tf.square(loss - 1))
        return loss

    def train_step(self, real_images):

        self.train_step_counter.assign_add(1)

        if self.phase == "TRANSITION":
            self.alpha.assign(
                tf.cast(self.train_step_counter / self.steps_per_epoch, tf.float32)
            )
        elif self.phase == "STABLE":
            self.alpha.assign(1.0)
        else:
            raise NotImplementedError
        alpha = tf.expand_dims(self.alpha, 0)
        batch_size = tf.shape(real_images)[0]
        real_labels = tf.ones(batch_size)
        fake_labels = -tf.ones(batch_size)

        z = tf.random.normal((batch_size, self.z_dim))
        const_input = tf.ones(tuple([batch_size] + list(self.g_input_shape)))
        noise = self.generate_noise(batch_size)
```

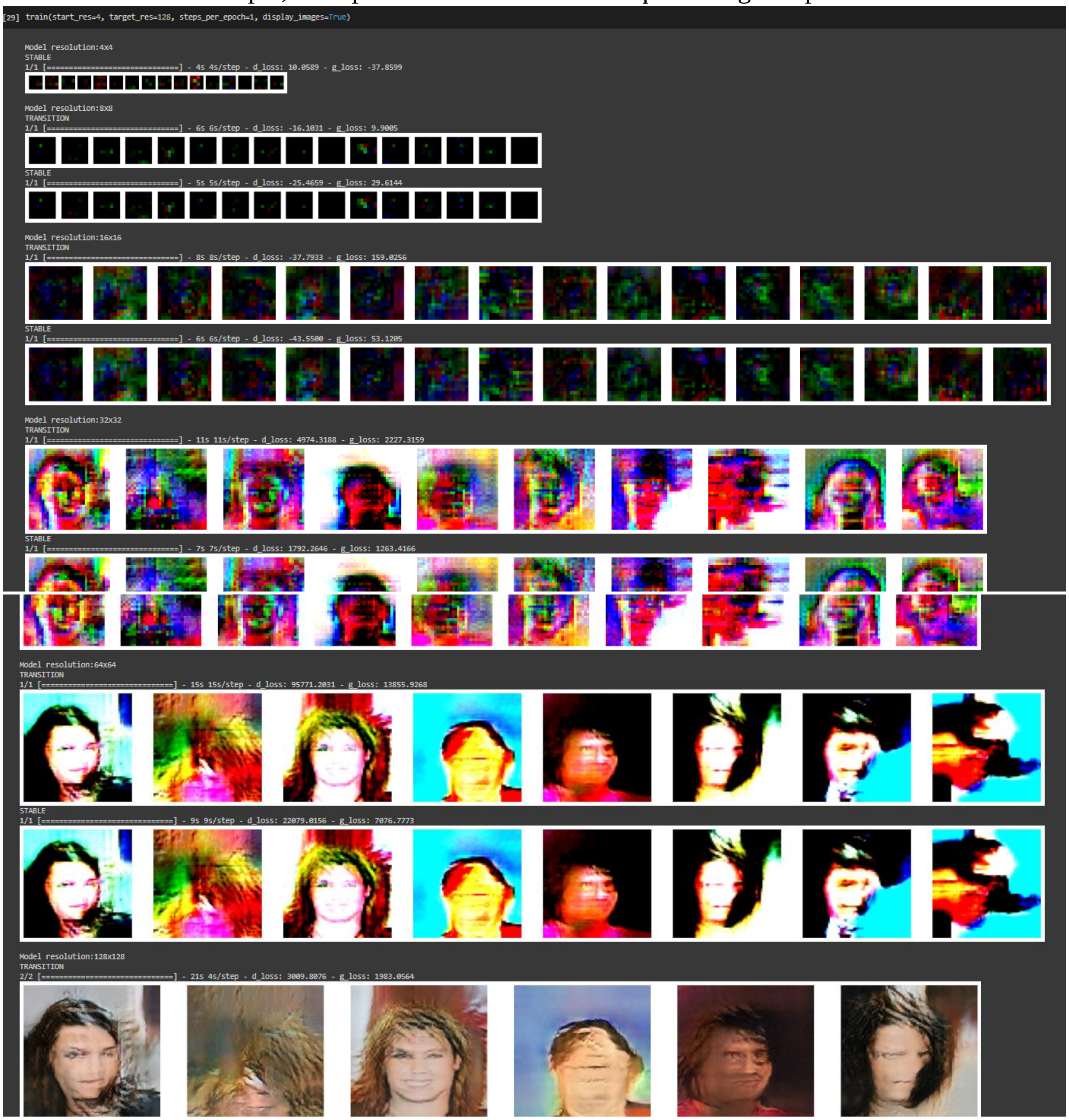
```python
    # generator
    with tf.GradientTape() as g_tape:
        w = self.mapping(z)
        fake_images = self.generator([const_input, w, noise, alpha])
        pred_fake = self.discriminator([fake_images, alpha])
        g_loss = wasserstein_loss(real_labels, pred_fake)

        trainable_weights = (
            self.mapping.trainable_weights + self.generator.trainable_weights
        )
        gradients = g_tape.gradient(g_loss, trainable_weights)
        self.g_optimizer.apply_gradients(zip(gradients, trainable_weights))

    # discriminator
    with tf.GradientTape() as gradient_tape, tf.GradientTape() as total_tape:
        # forward pass
        pred_fake = self.discriminator([fake_images, alpha])
        pred_real = self.discriminator([real_images, alpha])

        epsilon = tf.random.uniform((batch_size, 1, 1, 1))
        interpolates = epsilon * real_images + (1 - epsilon) * fake_images
        gradient_tape.watch(interpolates)
        pred_fake_grad = self.discriminator([interpolates, alpha])

        # calculate losses
        loss_fake = wasserstein_loss(fake_labels, pred_fake)
        loss_real = wasserstein_loss(real_labels, pred_real)
        loss_fake_grad = wasserstein_loss(fake_labels, pred_fake_grad)

        # gradient penalty
        gradients_fake = gradient_tape.gradient(loss_fake_grad, [interpolates])
        gradient_penalty = self.loss_weights[
            "gradient_penalty"
        ] * self.gradient_loss(gradients_fake)

        # drift loss
        all_pred = tf.concat([pred_fake, pred_real], axis=0)
        drift_loss = self.loss_weights["drift"] * tf.reduce_mean(all_pred ** 2)

        d_loss = loss_fake + loss_real + gradient_penalty + drift_loss

        gradients = total_tape.gradient(
            d_loss, self.discriminator.trainable_weights
        )
        self.d_optimizer.apply_gradients(
            zip(gradients, self.discriminator.trainable_weights)
        )

    # Update metrics
    self.d_loss_metric.update_state(d_loss)
    self.g_loss_metric.update_state(g_loss)
    return {
        "d_loss": self.d_loss_metric.result(),
        "g_loss": self.g_loss_metric.result(),
    }

f call(self, inputs: dict()):
    style_code = inputs.get("style_code", None)
    z = inputs.get("z", None)
    noise = inputs.get("noise", None)
    batch_size = inputs.get("batch_size", 1)
    alpha = inputs.get("alpha", 1.0)
    alpha = tf.expand_dims(alpha, 0)
    if style_code is None:
        if z is None:
            z = tf.random.normal((batch_size, self.z_dim))
        style_code = self.mapping(z)

    if noise is None:
        noise = self.generate_noise(batch_size)

    # self.alpha.assign(alpha)

    const_input = tf.ones(tuple([batch_size] + list(self.g_input_shape)))
    images = self.generator([const_input, style_code, noise, alpha])
    images = np.clip((images * 0.5 + 0.5) * 255, 0, 255).astype(np.uint8)

    return images
```

The section for training the model is defined. The model is first build at the smallest resolution then progressively grow the model to a higher resolution by combining the generator and discriminator blocks. The training happens in two phases, “transition” and “stable”. In the transition is where the previous features are incorporated with the current resolution which allows a smoother transition when scaling the resolution up. In fitting the model, each epoch is used as a phase.

```
START_RES = 4
TARGET_RES = 128

style_gan = StyleGAN(start_res=START_RES, target_res=TARGET_RES)
```

```
[17] def train(
         start_res=START_RES,
         target_res=TARGET_RES,
         steps_per_epoch=5000,
         display_images=True,
     ):
         opt_cfg = {"learning_rate": 1e-3, "beta_1": 0.0, "beta_2": 0.99, "epsilon": 1e-8}

         val_batch_size = 16
         val_z = tf.random.normal((val_batch_size, style_gan.z_dim))
         val_noise = style_gan.generate_noise(val_batch_size)

         start_res_log2 = int(np.log2(start_res))
         target_res_log2 = int(np.log2(target_res))

         for res_log2 in range(start_res_log2, target_res_log2 + 1):
             res = 2 ** res_log2
             for phase in ["TRANSITION", "STABLE"]:
                 if res == start_res and phase == "TRANSITION":
                     continue

                 train_dl = create_dataloader(res)

                 steps = int(train_step_ratio[res_log2] * steps_per_epoch)

                 style_gan.compile(
                     d_optimizer=tf.keras.optimizers.Adam(**opt_cfg),
                     g_optimizer=tf.keras.optimizers.Adam(**opt_cfg),
                     loss_weights={"gradient_penalty": 10, "drift": 0.001},
                     steps_per_epoch=steps,
                     res=res,
                     phase=phase,
                     run_eagerly=False,
                 )

                 prefix = f"res_{res}x{res}_{style_gan.phase}"

                 ckpt_cb = keras.callbacks.ModelCheckpoint(
                     f"checkpoints/stylegan_{res}x{res}.ckpt",
                     save_weights_only=True,
                     verbose=0,
                 )
                 print(phase)
                 style_gan.fit(
                     train_dl, epochs=1, steps_per_epoch=steps, callbacks=[ckpt_cb]
                 )

                 if display_images:
                     images = style_gan({"z": val_z, "noise": val_noise, "alpha": 1.0})
                     plot_images(images, res_log2)
```

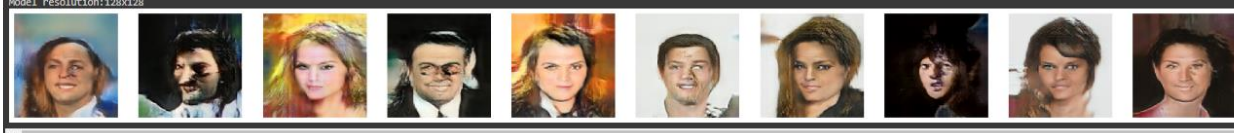
This is the sample progression every epoch, where 2 phases occur in each. This is just the initial sample, to improve the results would require a higher epoch.



Given the time constraints of training the images, results can be shown using pretrained 64x64 checkpoints.

```
url = "https://github.com/soon-yau/stylegan_keras/releases/download/keras_example_v1.0/stylegan_128x128.ckpt.zip"

weights_path = keras.utils.get_file(
    "stylegan_128x128.ckpt.zip",
    url,
    extract=True,
    cache_dir=os.path.abspath("."),
    cache_subdir="pretrained",
)

style_gan.grow_model(128)
style_gan.load_weights(os.path.join("pretrained/stylegan_128x128.ckpt"))

tf.random.set_seed(369420)
batch_size = 50
z = tf.random.normal((batch_size, style_gan.z_dim))
w = style_gan.mapping(z)
noise = style_gan.generate_noise(batch_size=batch_size)
images = style_gan({"style_code": w, "noise": noise, "alpha": 1.0})
plot_images(images, 5)
```

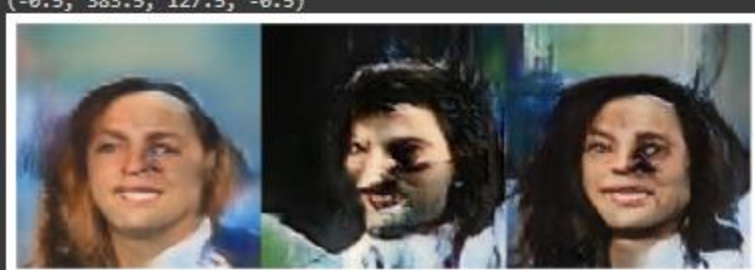
```
WARNING:tensorflow:Inconsistent references when loading the checkpoint into this object graph. For example, in the saved checkpoint object, `model.layer.weight` and `model.layer_copy.weight` reference the same variable, w
WARNING:tensorflow:Inconsistent references when loading the checkpoint into this object graph. For example, in the saved checkpoint object, `model.layer.weight` and `model.layer_copy.weight` reference the same variable, w

Model resolution:128x128
```



Images produced can also be mixed to create a new image containing the style of one of the input images.

```
alpha = 0.4
w_mix = np.expand_dims(alpha * w[0] + (1 - alpha) * w[1], 0)
noise_a = [np.expand_dims(n[0], 0) for n in noise]
mix_images = style_gan({"style_code": w_mix, "noise": noise_a})
image_row = np.hstack([images[0], images[1], mix_images[0]])
plt.figure(figsize=(9, 3))
plt.imshow(image_row)
plt.axis("off")
```

```
(-0.5, 383.5, 127.5, -0.5)
```



In conclusion, StyleGAN utilizes an alternative generator network which it borrows from style transfer literature, in particular, the use of instance normalization. It proposes changes to the generator model, incorporating mapping networks to map points throughout the latent space. It also uses a form of regularization called mixing regularization which mixes the 2 style variables during training. This exercise aims to generate computerized celebrity face images from scratch using the celeb_a dataset as the input dataset. Images can also be mixed to create new images containing the style and features of the 2 inputs.

References:

https://keras.io/examples/generative/stylegan/