monet-or-not-monet

April 20, 2024

0.1 Monet, or not Monet?

This project investigates the application of Generative Adversarial Networks (GANs) for artistic image creation, specifically targeting the generation of artworks inspired by the Impressionist master, Claude Monet.

GANs are a powerful deep learning architecture comprised of two competing neural networks:

Generator Network: This network acts as the creative force, tasked with generating novel images that adhere to the desired artistic style (Monet in this case). Discriminator Network: Functioning as the art critic, this network aims to accurately distinguish between real Monet paintings and the images produced by the generator network. The training process leverages an adversarial paradigm. The generator network continuously refines its ability to produce art that deceives the discriminator network. Conversely, the discriminator network strives to improve its proficiency in identifying forgeries generated by the generator.

This dynamic relationship fosters a training environment where both networks progressively enhance their performance.

[ ]:
```
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
#import tensorflow_addons as tfa
import matplotlib.pyplot as plt
import numpy as np

'''
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

'''
```

```
2024-03-08 04:45:15.810971: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-03-08 04:45:15.811122: E
```

```
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-03-08 04:45:16.079659: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
```

[ ]:
```
"\nimport os\nfor dirname, _, filenames in os.walk('/kaggle/input'):\n    for
filename in filenames:\n        print(os.path.join(dirname, filename))\n\n"
```

[ ]:
```
try:
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
    print('Device:', tpu.master())
    tf.config.experimental_connect_to_cluster(tpu)
    tf.tpu.experimental.initialize_tpu_system(tpu)
    strategy = tf.distribute.experimental.TPUStrategy(tpu)
except:
    strategy = tf.distribute.get_strategy()
print('Number of replicas:', strategy.num_replicas_in_sync)

AUTOTUNE = tf.data.experimental.AUTOTUNE
```

```
Number of replicas: 1
```

[ ]:
```
MONET_FILENAMES = tf.io.gfile.glob(str('/kaggle/input/gan-getting-started/
 ↪monet_tfrec/*.tfrec'))
print('Monet TFRecord Files:', len(MONET_FILENAMES))

PHOTO_FILENAMES = tf.io.gfile.glob(str('/kaggle/input/gan-getting-started/
 ↪photo_tfrec/*.tfrec'))
print('Photo TFRecord Files:', len(PHOTO_FILENAMES))
```

```
Monet TFRecord Files: 5
Photo TFRecord Files: 20
```

[ ]:
```
IMAGE_SIZE = [256, 256]

def decode_image(image):
    image = tf.image.decode_jpeg(image, channels=3)
    image = (tf.cast(image, tf.float32) / 127.5) - 1
    image = tf.reshape(image, [*IMAGE_SIZE, 3])
    return image

def read_tfrecord(example):
    tfrecord_format = {
        "image_name": tf.io.FixedLenFeature([], tf.string),
        "image": tf.io.FixedLenFeature([], tf.string),
```

```
        "target": tf.io.FixedLenFeature([], tf.string)
    }
    example = tf.io.parse_single_example(example, tfrecord_format)
    image = decode_image(example['image'])
    return image
```

[ ]:
```
def load_dataset(filenames, labeled=True, ordered=False):
    dataset = tf.data.TFRecordDataset(filenames)
    dataset = dataset.map(read_tfrecord, num_parallel_calls=AUTOTUNE)
    return dataset
```

[ ]:
```
monet_ds = load_dataset(MONET_FILENAMES, labeled=True).batch(1)
photo_ds = load_dataset(PHOTO_FILENAMES, labeled=True).batch(1)
```

0.1.1 EDA

This is a quick overview of the images and the structure of the data.

The images are 250x250 pixels and can create a 250x250 pixel paintings.

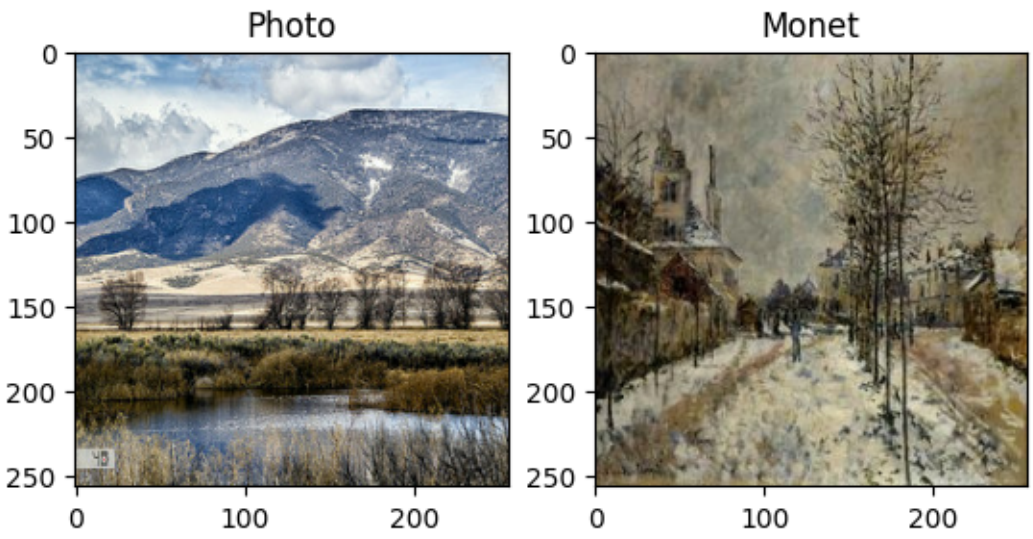
As this is an unsupervised learning algorithm there is less data anlysis needed.

[ ]:
```
example_monet = next(iter(monet_ds))
example_photo = next(iter(photo_ds))

plt.subplot(121)
plt.title('Photo')
plt.imshow(example_photo[0] * 0.5 + 0.5)

plt.subplot(122)
plt.title('Monet')
plt.imshow(example_monet[0] * 0.5 + 0.5)
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7e532c0b0d30>
```



0.1.2 Model Architecture

For this use case a GAN makes the most sense as it takes a generator and a discriminator that train against each other to model a specific style of artwork.

[ ]:
```
OUTPUT_CHANNELS = 3

def downsample(filters, size, apply_instancenorm=True):
    initializer = tf.random_normal_initializer(0., 0.02)
    gamma_init = keras.initializers.RandomNormal(mean=0.0, stddev=0.02)

    result = keras.Sequential()
    result.add(layers.Conv2D(filters, size, strides=2, padding='same',
                             kernel_initializer=initializer, use_bias=False))

    if apply_instancenorm:
        result.add(tf.keras.layers.
 ↪GroupNormalization(gamma_initializer=gamma_init))

    result.add(layers.LeakyReLU())

    return result
```

[ ]:
```
def upsample(filters, size, apply_dropout=False):
    initializer = tf.random_normal_initializer(0., 0.02)
    gamma_init = keras.initializers.RandomNormal(mean=0.0, stddev=0.02)

    result = keras.Sequential()
    result.add(layers.Conv2DTranspose(filters, size, strides=2,
```

```
                                    padding='same',
                                    kernel_initializer=initializer,
                                    use_bias=False))

    result.add(tf.keras.layers.GroupNormalization(gamma_initializer=gamma_init))

    if apply_dropout:
        result.add(layers.Dropout(0.5))

    result.add(layers.ReLU())

    return result
```

[ ]:
```
def Generator():
    inputs = layers.Input(shape=[256,256,3])

    # bs = batch size
    down_stack = [
        downsample(64, 4, apply_instancenorm=False), # (bs, 128, 128, 64)
        downsample(128, 4), # (bs, 64, 64, 128)
        downsample(256, 4), # (bs, 32, 32, 256)
        downsample(512, 4), # (bs, 16, 16, 512)
        downsample(512, 4), # (bs, 8, 8, 512)
        downsample(512, 4), # (bs, 4, 4, 512)
        downsample(512, 4), # (bs, 2, 2, 512)
        downsample(512, 4), # (bs, 1, 1, 512)
    ]

    up_stack = [
        upsample(512, 4, apply_dropout=True), # (bs, 2, 2, 1024)
        upsample(512, 4, apply_dropout=True), # (bs, 4, 4, 1024)
        upsample(512, 4, apply_dropout=True), # (bs, 8, 8, 1024)
        upsample(512, 4), # (bs, 16, 16, 1024)
        upsample(1024,4),
        upsample(512, 4, apply_dropout=True), # (bs, 8, 8, 1024)
        upsample(512, 4), # (bs, 16, 16, 1024)
        upsample(256, 4), # (bs, 32, 32, 512)
        upsample(128, 4), # (bs, 64, 64, 256)
        upsample(64, 4), # (bs, 128, 128, 128)
    ]

    initializer = tf.random_normal_initializer(0., 0.02)
    last = layers.Conv2DTranspose(OUTPUT_CHANNELS, 4,
                                  strides=2,
                                  padding='same',
                                  kernel_initializer=initializer,
                                  activation='tanh') # (bs, 256, 256, 3)
```

```
    x = inputs

    # Downsampling through the model
    skips = []
    for down in down_stack:
        x = down(x)
        skips.append(x)

    skips = reversed(skips[:-1])

    # Upsampling and establishing the skip connections
    for up, skip in zip(up_stack, skips):
        x = up(x)
        x = layers.Concatenate()([x, skip])

    x = last(x)

    return keras.Model(inputs=inputs, outputs=x)
```

[ ]:
```
def Discriminator():
    initializer = tf.random_normal_initializer(0., 0.02)
    gamma_init = keras.initializers.RandomNormal(mean=0.0, stddev=0.02)

    inp = layers.Input(shape=[256, 256, 3], name='input_image')

    x = inp

    down1 = downsample(64, 4, False)(x) # (bs, 128, 128, 64)
    down2 = downsample(128, 4)(down1) # (bs, 64, 64, 128)
    down3 = downsample(256, 4)(down2) # (bs, 32, 32, 256)
    down4 = downsample(512, 4)(down2) # (bs, 32, 32, 256)
    down4 = downsample(1024, 4)(down2) # (bs, 32, 32, 256)

    zero_pad1 = layers.ZeroPadding2D()(down3) # (bs, 34, 34, 256)
    conv = layers.Conv2D(512, 4, strides=1,
                         kernel_initializer=initializer,
                         use_bias=False)(zero_pad1) # (bs, 31, 31, 512)

    norm1 = tf.keras.layers.
↪GroupNormalization(gamma_initializer=gamma_init)(conv)

    leaky_relu = layers.LeakyReLU()(norm1)

    zero_pad2 = layers.ZeroPadding2D()(leaky_relu) # (bs, 33, 33, 512)

    last = layers.Conv2D(1, 4, strides=1,
```

```
                                kernel_initializer=initializer)(zero_pad2) # (bs, 30,␣
↪30, 1)

    return tf.keras.Model(inputs=inp, outputs=last)
```

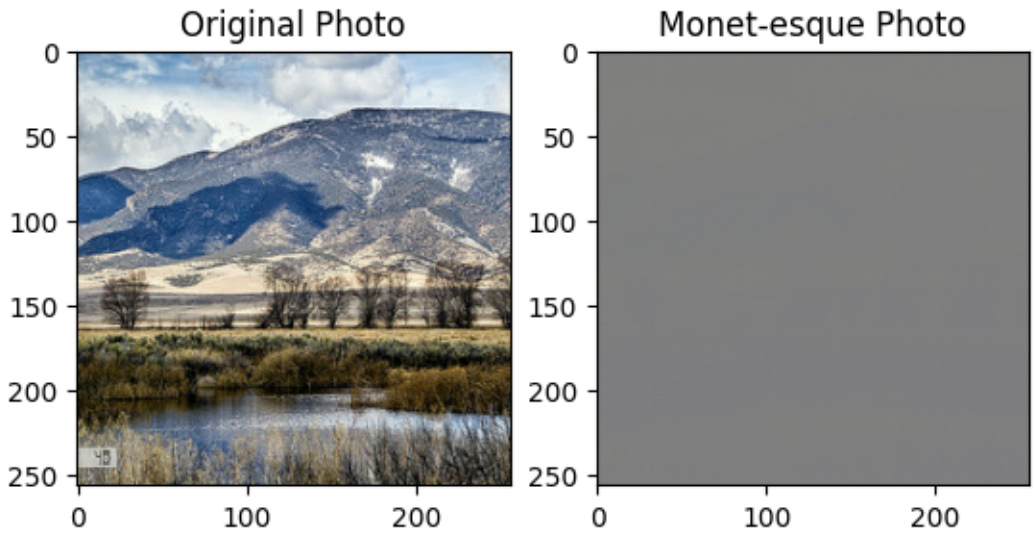
[ ]:
```
with strategy.scope():
    monet_generator = Generator() # transforms photos to Monet-esque paintings
    photo_generator = Generator() # transforms Monet paintings to be more like␣
↪photos

    monet_discriminator = Discriminator() # differentiates real Monet paintings␣
↪and generated Monet paintings
    photo_discriminator = Discriminator() # differentiates real photos and␣
↪generated photos
```

[ ]:
```
to_monet = monet_generator(example_photo)

plt.subplot(1, 2, 1)
plt.title("Original Photo")
plt.imshow(example_photo[0] * 0.5 + 0.5)

plt.subplot(1, 2, 2)
plt.title("Monet-esque Photo")
plt.imshow(to_monet[0] * 0.5 + 0.5)
plt.show()
```



[ ]:
```
class CycleGan(keras.Model):
    def __init__(
```

```
        self,
        monet_generator,
        photo_generator,
        monet_discriminator,
        photo_discriminator,
        lambda_cycle=10,
    ):
        super(CycleGan, self).__init__()
        self.m_gen = monet_generator
        self.p_gen = photo_generator
        self.m_disc = monet_discriminator
        self.p_disc = photo_discriminator
        self.lambda_cycle = lambda_cycle

    def compile(
        self,
        m_gen_optimizer,
        p_gen_optimizer,
        m_disc_optimizer,
        p_disc_optimizer,
        gen_loss_fn,
        disc_loss_fn,
        cycle_loss_fn,
        identity_loss_fn
    ):
        super(CycleGan, self).compile()
        self.m_gen_optimizer = m_gen_optimizer
        self.p_gen_optimizer = p_gen_optimizer
        self.m_disc_optimizer = m_disc_optimizer
        self.p_disc_optimizer = p_disc_optimizer
        self.gen_loss_fn = gen_loss_fn
        self.disc_loss_fn = disc_loss_fn
        self.cycle_loss_fn = cycle_loss_fn
        self.identity_loss_fn = identity_loss_fn

    def train_step(self, batch_data):
        real_monet, real_photo = batch_data

        with tf.GradientTape(persistent=True) as tape:
            # photo to monet back to photo
            fake_monet = self.m_gen(real_photo, training=True)
            cycled_photo = self.p_gen(fake_monet, training=True)

            # monet to photo back to monet
            fake_photo = self.p_gen(real_monet, training=True)
            cycled_monet = self.m_gen(fake_photo, training=True)
```

```
            # generating itself
            same_monet = self.m_gen(real_monet, training=True)
            same_photo = self.p_gen(real_photo, training=True)

            # discriminator used to check, inputing real images
            disc_real_monet = self.m_disc(real_monet, training=True)
            disc_real_photo = self.p_disc(real_photo, training=True)

            # discriminator used to check, inputing fake images
            disc_fake_monet = self.m_disc(fake_monet, training=True)
            disc_fake_photo = self.p_disc(fake_photo, training=True)

            # evaluates generator loss
            monet_gen_loss = self.gen_loss_fn(disc_fake_monet)
            photo_gen_loss = self.gen_loss_fn(disc_fake_photo)

            # evaluates total cycle consistency loss
            total_cycle_loss = self.cycle_loss_fn(real_monet, cycled_monet,␣
↪self.lambda_cycle) + self.cycle_loss_fn(real_photo, cycled_photo, self.
↪lambda_cycle)

            # evaluates total generator loss
            total_monet_gen_loss = monet_gen_loss + total_cycle_loss + self.
↪identity_loss_fn(real_monet, same_monet, self.lambda_cycle)
            total_photo_gen_loss = photo_gen_loss + total_cycle_loss + self.
↪identity_loss_fn(real_photo, same_photo, self.lambda_cycle)

            # evaluates discriminator loss
            monet_disc_loss = self.disc_loss_fn(disc_real_monet,␣
↪disc_fake_monet)
            photo_disc_loss = self.disc_loss_fn(disc_real_photo,␣
↪disc_fake_photo)

        # Calculate the gradients for generator and discriminator
        monet_generator_gradients = tape.gradient(total_monet_gen_loss,
                                                  self.m_gen.
↪trainable_variables)
        photo_generator_gradients = tape.gradient(total_photo_gen_loss,
                                                  self.p_gen.
↪trainable_variables)

        monet_discriminator_gradients = tape.gradient(monet_disc_loss,
                                                      self.m_disc.
↪trainable_variables)
        photo_discriminator_gradients = tape.gradient(photo_disc_loss,
```

```
                                                    self.p_disc.
↪trainable_variables)

        # Apply the gradients to the optimizer
        self.m_gen_optimizer.apply_gradients(zip(monet_generator_gradients,
                                                 self.m_gen.
↪trainable_variables))

        self.p_gen_optimizer.apply_gradients(zip(photo_generator_gradients,
                                                 self.p_gen.
↪trainable_variables))

        self.m_disc_optimizer.apply_gradients(zip(monet_discriminator_gradients,
                                                  self.m_disc.
↪trainable_variables))

        self.p_disc_optimizer.apply_gradients(zip(photo_discriminator_gradients,
                                                  self.p_disc.
↪trainable_variables))

        return {
            "monet_gen_loss": total_monet_gen_loss,
            "photo_gen_loss": total_photo_gen_loss,
            "monet_disc_loss": monet_disc_loss,
            "photo_disc_loss": photo_disc_loss
        }
```

[ ]:
```
with strategy.scope():
    def discriminator_loss(real, generated):
        real_loss = tf.keras.losses.BinaryCrossentropy(from_logits=True,␣
↪reduction=tf.keras.losses.Reduction.NONE)(tf.ones_like(real), real)

        generated_loss = tf.keras.losses.BinaryCrossentropy(from_logits=True,␣
↪reduction=tf.keras.losses.Reduction.NONE)(tf.zeros_like(generated),␣
↪generated)

        total_disc_loss = real_loss + generated_loss

        return total_disc_loss * 0.5
```

[ ]:
```
with strategy.scope():
    def generator_loss(generated):
        return tf.keras.losses.BinaryCrossentropy(from_logits=True,␣
↪reduction=tf.keras.losses.Reduction.NONE)(tf.ones_like(generated), generated)
```

[ ]:
```
with strategy.scope():
    def calc_cycle_loss(real_image, cycled_image, LAMBDA):
        loss1 = tf.reduce_mean(tf.abs(real_image - cycled_image))

        return LAMBDA * loss1
```

[ ]:
```
with strategy.scope():
    def identity_loss(real_image, same_image, LAMBDA):
        loss = tf.reduce_mean(tf.abs(real_image - same_image))
        return LAMBDA * 0.5 * loss
```

[ ]:
```
with strategy.scope():
    monet_generator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)
    photo_generator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)

    monet_discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)
    photo_discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)
```

[ ]:
```
with strategy.scope():
    cycle_gan_model = CycleGan(
        monet_generator, photo_generator, monet_discriminator,␣
 ↪photo_discriminator
    )

    cycle_gan_model.compile(
        m_gen_optimizer = monet_generator_optimizer,
        p_gen_optimizer = photo_generator_optimizer,
        m_disc_optimizer = monet_discriminator_optimizer,
        p_disc_optimizer = photo_discriminator_optimizer,
        gen_loss_fn = generator_loss,
        disc_loss_fn = discriminator_loss,
        cycle_loss_fn = calc_cycle_loss,
        identity_loss_fn = identity_loss
    )
```

[ ]:
```
cycle_gan_model.fit(
    tf.data.Dataset.zip((monet_ds, photo_ds)),
    epochs=10
)
```

```
Epoch 1/10

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1709873302.333878     128 device_compiler.h:186] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

300/300            333s 572ms/step -
```

```
monet_disc_loss: 0.5746 - monet_gen_loss: 5.7664 - photo_disc_loss: 0.5516 -
photo_gen_loss: 5.8791 - loss: 0.0000e+00
Epoch 2/10

/opt/conda/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of
data; interrupting training. Make sure that your dataset or generator can
generate at least `steps_per_epoch * epochs` batches. You may need to use the
`.repeat()` function when building your dataset.
  self.gen.throw(typ, value, traceback)

300/300             171s 569ms/step -
monet_disc_loss: 0.5941 - monet_gen_loss: 3.9958 - photo_disc_loss: 0.6298 -
photo_gen_loss: 3.9536 - loss: 0.0000e+00
Epoch 3/10
149/300             1:26 570ms/step -
monet_disc_loss: 0.6219 - monet_gen_loss: 3.8039 - photo_disc_loss: 0.6301 -
photo_gen_loss: 3.7763
```

0.1.3 Results and Analysis

Results will be created off of an image set that neither the generator or discriniator have seen then ranked by a an algorithim called MiFID. MiFID uses the minimum cosine distance of all training samples in the feature space then averages across all samples to create a score of how well the GAN works to create monet like paintings. The lower the score the better the model. This model has been evaluated at 76.12. The generator and discrimantor both worked well allowing for above average for the kagle competition. I find this to be very encouraging. I think that using more layers and using a deticated GPU would create even better results

0.1.4 Conclusion

Generative Adversial Networks are a very interesting way of creating generative AI artwork. When you have an expressed purpose realativly small use case for a more expansive generative AI solution you would need much more data and layers to the model that could create artwork of any artist or use case. This was a fun and educational way to interact with generative AI as it is becomming a more and more influential part of our daily lives.

Submission

[ ]:
```
_, ax = plt.subplots(5, 2, figsize=(12, 12))
for i, img in enumerate(photo_ds.take(5)):
    prediction = monet_generator(img, training=False)[0].numpy()
    prediction = (prediction * 127.5 + 127.5).astype(np.uint8)
    img = (img[0] * 127.5 + 127.5).numpy().astype(np.uint8)

    ax[i, 0].imshow(img)
    ax[i, 1].imshow(prediction)
    ax[i, 0].set_title("Input Photo")
    ax[i, 1].set_title("Monet-esque")
    ax[i, 0].axis("off")
    ax[i, 1].axis("off")
```

```
plt.show()
```

[ ]:
```
import PIL
! mkdir ../images
```

[ ]:
```
import shutil
shutil.make_archive("/kaggle/working/images", 'zip', "/kaggle/images")
```

[ ]:
```
i = 1
for img in photo_ds:
    prediction = monet_generator(img, training=False)[0].numpy()
    prediction = (prediction * 127.5 + 127.5).astype(np.uint8)
    im = PIL.Image.fromarray(prediction)
    im.save("../images/" + str(i) + ".jpg")
    i += 1
```