Lab 8 - PCC177/BCC406

REDES NEURAIS E APRENDIZAGEM EM PROFUNDIDADE

Modelos Generativos

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Objetivos:

- Parte I : Compressão com AE
- Parte II : Detecção de anomalias
- Parte III: Redes Generativas Adversariais

Data da entrega : 12/12/23

- Complete o código (marcado com ToDo) e quando requisitado, escreva textos diretamente nos notebooks. Onde tiver *None*, substitua pelo seu código.
- Execute todo notebook e salve tudo em um PDF **nomeado** como "NomeSobrenome-Lab.pdf"
- Envie o PDF via google [FORM]

Este notebook é baseado em tensorflow e Keras.

Parte I: Autoencoder para redução de dimensionalidade (30pt)

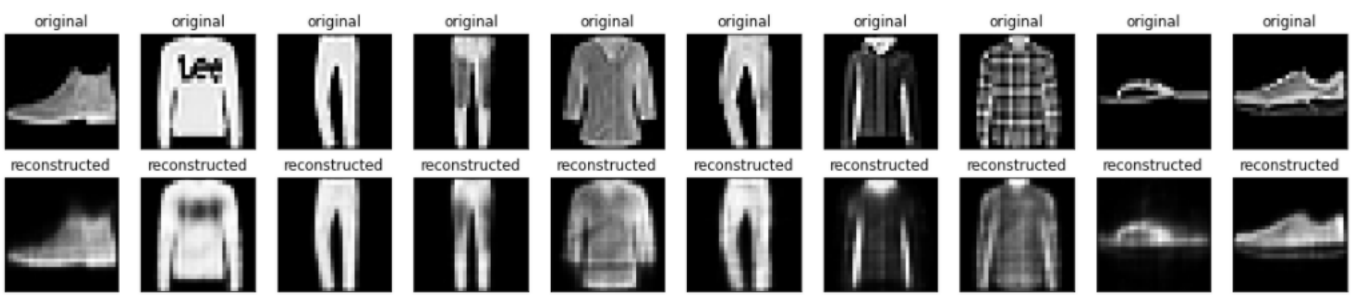
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf

from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.model_selection import train_test_split
from tensorflow.keras import layers, losses
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.models import Model
```

Carrega dataset Fashon MNIST dataset. Cada imagem tem resolução 28x28 pixels.

```
(x_train, _), (x_test, _) = fashion_mnist.load_data()

x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.

print (x_train.shape)
print (x_test.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
29515/29515 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
26421880/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
5148/5148 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4422102/4422102 [==============================] - 0s 0us/step
(60000, 28, 28)
(10000, 28, 28)
```

Exemplo de classes



Abaixo exemplo de implementação de autoencoder apena com camadas densas. O `encoder`, comprime as imegns em 4 dimensões (latent_dim), e o `decoder` reconstróe a imagem a partir do vetor latente.

O exemplo abaixo usa a [Keras Model Subclassing API](https://www.tensorflow.org/guide/keras/custom_layers_and_models).

```
latent_dims = [2, 4, 8, 16, 64]

class Autoencoder(Model):
  def __init__(self, latent_dim):
    super(Autoencoder, self).__init__()
    self.latent_dim = latent_dim
    self.encoder = tf.keras.Sequential([
      layers.Flatten(),
      layers.Dense(latent_dim, activation='relu'),
    ])
    self.decoder = tf.keras.Sequential([
      layers.Dense(784, activation='sigmoid'),
      layers.Reshape((28, 28))
    ])

  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded

autoencoders = []

for dim in latent_dims:
    autoencoder = Autoencoder(latent_dim=dim)
    autoencoder.compile(optimizer='adam', loss=losses.MeanSquaredError())
    autoencoder.fit(x_train, x_train, epochs=10, shuffle=True, validation_data=(x_test, x_test))
    autoencoders.append(autoencoder)
```

```
Epoch 2/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0254 - val_loss: 0.0242
Epoch 3/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0239 - val_loss: 0.0237
Epoch 4/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0235 - val_loss: 0.0234
Epoch 5/10
1875/1875 [==============================] - 6s 3ms/step - loss: 0.0233 - val_loss: 0.0233
```

```
Epoch 7/10
1875/1875 [==============================] - 6s 3ms/step - loss: 0.0089 - val_loss: 0.0089
Epoch 8/10
1875/1875 [==============================] - 8s 4ms/step - loss: 0.0088 - val_loss: 0.0088
Epoch 9/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0087 - val_loss: 0.0088
Epoch 10/10
1875/1875 [==============================] - 7s 4ms/step - loss: 0.0087 - val_loss: 0.0088
```

Treine o modelo e veja os resultados da re-construção.

```
# Exibição das imagens para todos os modelos em uma única figura
n_models = len(latent_dims)
n_images = 10
vertical_space = 2

plt.figure(figsize=(20, (4 + vertical_space) * n_models))

for i, (dim, autoencoder) in enumerate(zip(latent_dims, autoencoders), 1):
    encoded_imgs = autoencoder.encoder(x_test).numpy()
    decoded_imgs = autoencoder.decoder(encoded_imgs).numpy()

    #plt.text(n_images // 2, -1, f'Latent Dim: {dim}', ha='center', va='center', fontsize=12)

    for j in range(n_images):
        # display original
        ax = plt.subplot(n_models * 2, n_images, (i-1) * (n_images * 2) + j + 1)
        plt.imshow(x_test[j])
        plt.title("Original")
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

    for j in range(n_images):
        # display reconstruction
        ax = plt.subplot(n_models * 2, n_images, (i-1) * (n_images * 2) + n_images + j + 1)
        plt.imshow(decoded_imgs[j])
        plt.title("Reconstructed")
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

plt.show()
```


Original Original Original Original Original Original Original Original Original Original
Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed
Original Original Original Original Original Original Original Original Original Original
Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed
Original Original Original Original Original Original Original Original Original Original
Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed
Original Original Original Original Original Original Original Original Original Original
Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed
Original Original Original Original Original Original Original Original Original Original
Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed

ToDo : Testes (15pt)

Faça testes com vetor latente de dimensões 2, 8, 16 e 64.

Os testes foram realizados no próprio código acima mudando para imprimir todos os modelos com o vetor latente de dimensões diferentes.

ToDo : Responda (15pt)

Escreva suas conclusões sobre os testes executados

Quanto maior for o vetor latente, melhor será a reconstrução da imagem.

Parte II: Detecção de anomalias (30pt)

Intro

Neste exemplo, você vai detectar anomalis em sinaos de eletrocardiograma (ECG). Para tal, treine um autoencoder no dataset [ECG5000 dataset](). Este dataset contém 5000 batimentos de ECG (https://en.wikipedia.org/wiki/Electrocardiography), cada um com 140 amostras (pontos) na curva. Cada instância da base de dados (um batimento) foi rotulado como zero (0) ou um (1). A classe zero corresponde a um batimento anormal e a classe um a um batimento de classe normal. Queremos identificar os anormais.

Para detectar anomalias usando um autoencoder você deve treinar um autoencoder apenas em batimentos normais. Ele vai aprender a re-construir os batimentos saudáveis. A hipóteses é que os batimentos anormais vão divergir no padrão, quando compararmos a entrada com a re-construção.

Carrega base de ECG

Base de dados detalhada no site: timeseriesclassification.com.

```
# Download the dataset
dataframe = pd.read_csv('http://storage.googleapis.com/download.tensorflow.org/data/ecg.csv', header=None)
raw_data = dataframe.values
dataframe.head()
```

	0	1	2	3	4	5	6	7	
0	-0.112522	-2.827204	-3.773897	-4.349751	-4.376041	-3.474986	-2.181408	-1.818286	-
1	-1.100878	-3.996840	-4.285843	-4.506579	-4.022377	-3.234368	-1.566126	-0.992258	-
2	-0.567088	-2.593450	-3.874230	-4.584095	-4.187449	-3.151462	-1.742940	-1.490659	-
3	0.490473	-1.914407	-3.616364	-4.318823	-4.268016	-3.881110	-2.993280	-1.671131	-
4	0.800232	-0.874252	-2.384761	-3.973292	-4.338224	-3.802422	-2.534510	-1.783423	-

5 rows × 141 columns

```
# The last element contains the labels
labels = raw_data[:, -1]

# The other data points are the electrocadriogram data
data = raw_data[:, 0:-1]

train_data, test_data, train_labels, test_labels = train_test_split(
    data, labels, test_size=0.2, random_state=21
)
```

Normaliza entre `[0,1]`.

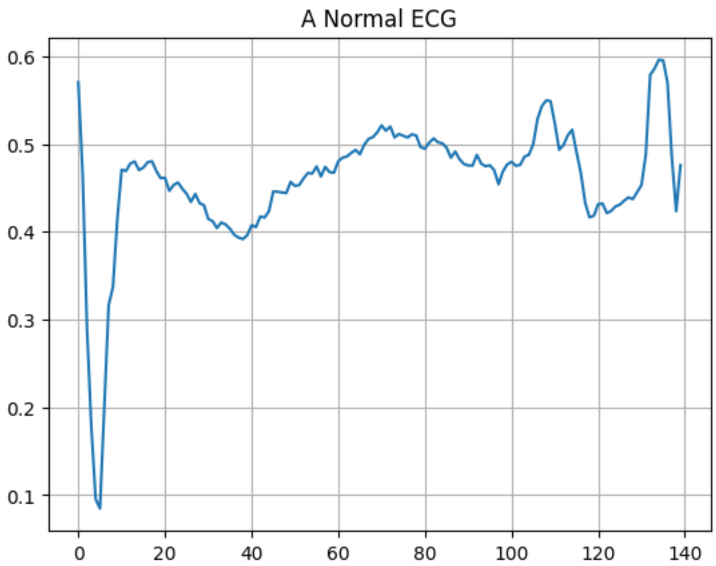
```
min_val = tf.reduce_min(train_data)
max_val = tf.reduce_max(train_data)

train_data = (train_data - min_val) / (max_val - min_val)
test_data = (test_data - min_val) / (max_val - min_val)

train_data = tf.cast(train_data, tf.float32)
test_data = tf.cast(test_data, tf.float32)
```

Vamos separar os batimentos normais (label 1) para treinar o Autoencoder.

```
train_labels = train_labels.astype(bool)
test_labels = test_labels.astype(bool)

normal_train_data = train_data[train_labels]
normal_test_data = test_data[test_labels]

anomalous_train_data = train_data[~train_labels]
anomalous_test_data = test_data[~test_labels]
```

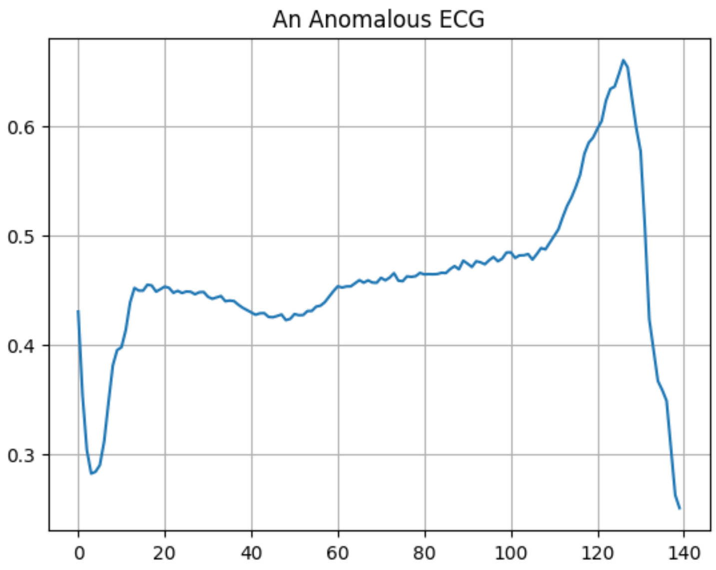
Plote um batimento normal.

```
plt.grid()
plt.plot(np.arange(140), normal_train_data[0])
plt.title("A Normal ECG")
plt.show()
```



Plote um batimento anômalo.

```
plt.grid()
plt.plot(np.arange(140), anomalous_train_data[0])
plt.title("An Anomalous ECG")
plt.show()
```



ToDo : Construção de um modelo (30pt)

Construa um modelo. Primeiramente tente construir apenas com camadas densas. Depois, tente construir um modelo com camadas de convolução de uma dimensão (Lembre-se que um sinal de ECG é uma série temporal de uma dimensão). [Conv1D]

```
class AnomalyDetector(Model):
  def __init__(self):
    super(AnomalyDetector, self).__init__()
    self.encoder = tf.keras.Sequential([
        layers.Flatten(),
        layers.Dense(32, activation='relu'),
        layers.Dense(16, activation='relu'),
        layers.Dense(8, activation='relu'),
    ])

    self.decoder = tf.keras.Sequential([
        layers.Dense(16, activation='relu'),
        layers.Dense(32, activation='relu'),
        layers.Dense(140, activation='sigmoid'),  # Output size should match input size
        layers.Reshape((140, 1))
    ])

    def call(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded


  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded

autoencoder = AnomalyDetector()
```

```
autoencoder.compile(optimizer='adam', loss='mae')
```

Depois de treinar com os batimentos normais, avalie com os anormais.

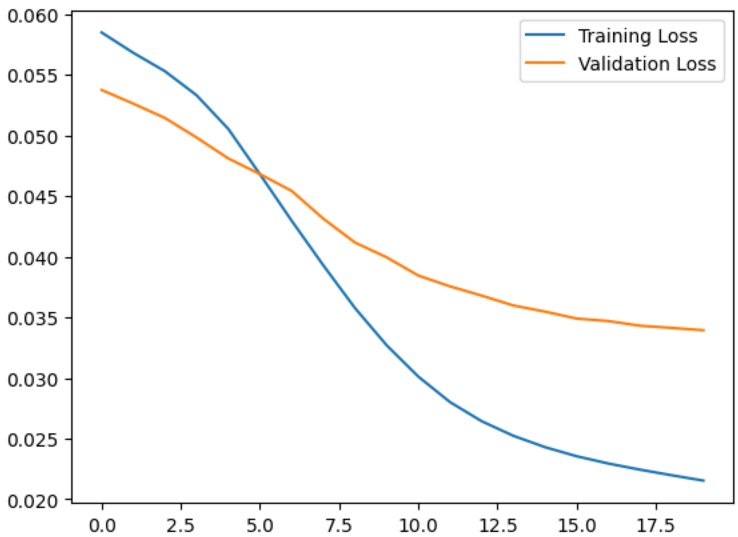
```
history = autoencoder.fit(normal_train_data, normal_train_data,
          epochs=20,
          batch_size=512,
          validation_data=(test_data, test_data),
          shuffle=True)
```

```
Epoch 1/20
5/5 [==============================] - 2s 46ms/step - loss: 0.0585 - val_loss: 0.0537
Epoch 2/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0568 - val_loss: 0.0526
Epoch 3/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0553 - val_loss: 0.0514
Epoch 4/20
```

```
5/5 [==============================] - 0s 14ms/step - loss: 0.0533 - val_loss: 0.0498
Epoch 5/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0505 - val_loss: 0.0481
Epoch 6/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0468 - val_loss: 0.0468
Epoch 7/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0430 - val_loss: 0.0454
Epoch 8/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0393 - val_loss: 0.0431
Epoch 9/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0358 - val_loss: 0.0412
Epoch 10/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0327 - val_loss: 0.0399
Epoch 11/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0301 - val_loss: 0.0384
Epoch 12/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0280 - val_loss: 0.0376
Epoch 13/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0264 - val_loss: 0.0368
Epoch 14/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0252 - val_loss: 0.0360
Epoch 15/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0243 - val_loss: 0.0355
Epoch 16/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0235 - val_loss: 0.0349
Epoch 17/20
5/5 [==============================] - 0s 14ms/step - loss: 0.0229 - val_loss: 0.0347
Epoch 18/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0224 - val_loss: 0.0343
Epoch 19/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0220 - val_loss: 0.0341
Epoch 20/20
5/5 [==============================] - 0s 10ms/step - loss: 0.0215 - val_loss: 0.0339
```

```
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
```

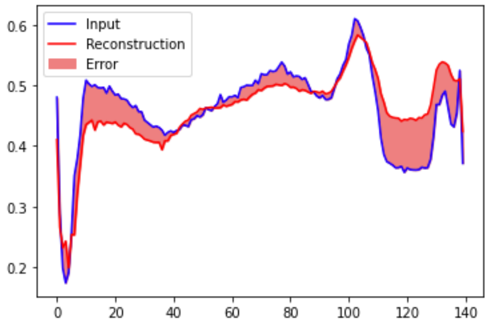
```
<matplotlib.legend.Legend at 0x7b985017ba90>
```



Você vai considerar um batimento como anômalo se ele divergir masi que um desvio padrão das amostras normais. Primeiro, vamos plotar um batimento normal a partir da base de treino e sua reconstrução. Assim, poderemos calcular o erro de re-construção.

```
encoded_data = autoencoder.encoder(tf.reshape(normal_test_data, (-1, 140))).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()


plt.plot(normal_test_data[0], 'b')
plt.plot(decoded_data[0], 'r')

decoded_data = np.squeeze(decoded_data)

plt.fill_between(np.arange(140), decoded_data[0], normal_test_data[0], color='lightcoral')
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```

Imagem esperada:



Vamos fazer o mesmo para um batimento anômalo.

```
encoded_data = autoencoder.encoder(anomalous_test_data).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()

plt.plot(anomalous_test_data[0], 'b')
plt.plot(decoded_data[0], 'r')
decoded_data = np.squeeze(decoded_data)
plt.fill_between(np.arange(140), decoded_data[0], anomalous_test_data[0], color='lightcoral')
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```

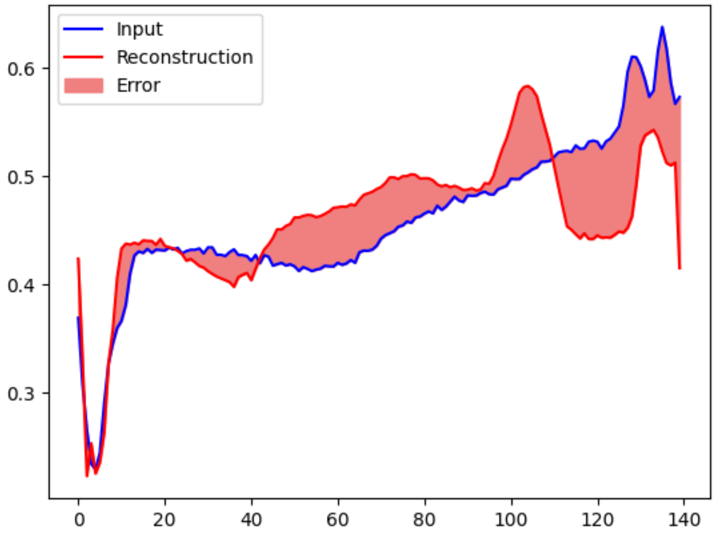
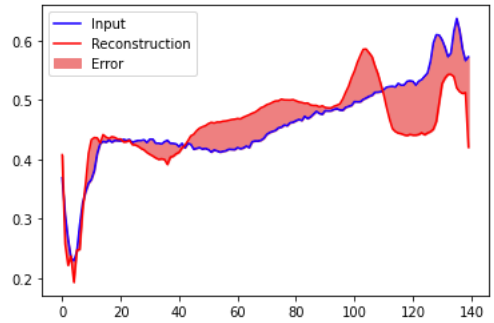


Imagem esperada:



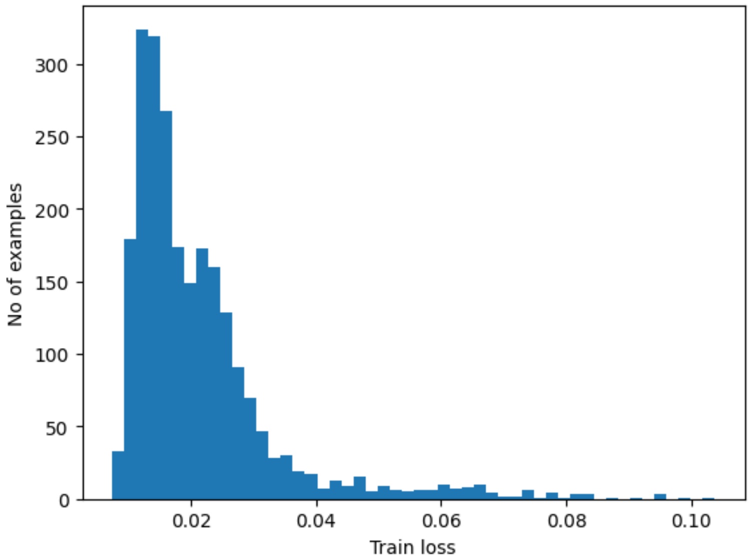
Detectando as anomalias

Vamos detectar as anomalis se o erro de reconstrução for maior que um limiar. Aqui, vamos calcular o erro médio para os exemp;los normais do treino e depois, classificar os anormais do teste, que tenha erro de reconstrução maior que um desvio padrão.

Plota erro de reconstrução de batimentos normais do treino

```
reconstructions = autoencoder.predict(normal_train_data)
reconstructions = tf.squeeze(reconstructions, axis=-1)

train_loss = tf.keras.losses.mae(reconstructions, normal_train_data)

plt.hist(train_loss[None,:], bins=50)
plt.xlabel("Train loss")
plt.ylabel("No of examples")
plt.show()
```

```
74/74 [==============================] - 0s 2ms/step
```



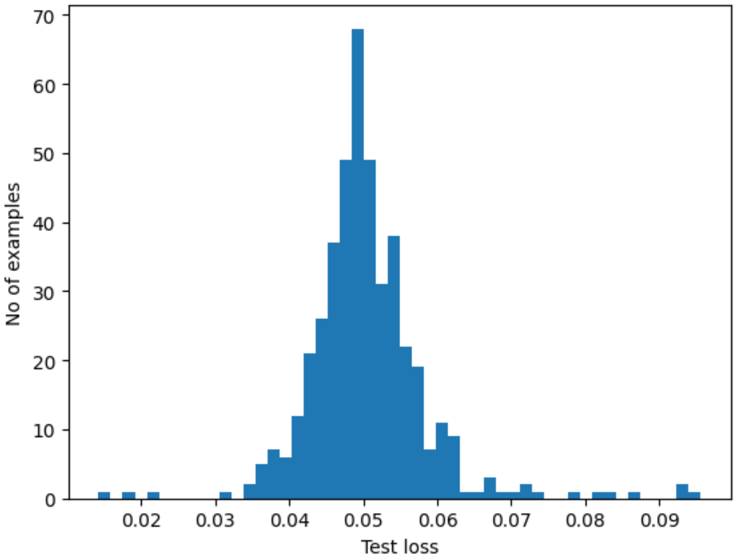
Escolha do limiar.

```
threshold = np.mean(train_loss) + np.std(train_loss)
print("Threshold: ", threshold)
```

```
Threshold:  0.03356406
```

```
reconstructions = autoencoder.predict(anomalous_test_data)
reconstructions = tf.squeeze(reconstructions, axis=-1)
test_loss = tf.keras.losses.mae(reconstructions, anomalous_test_data)

plt.hist(test_loss[None, :], bins=50)
plt.xlabel("Test loss")
plt.ylabel("No of examples")
plt.show()
```

```
14/14 [==============================] - 0s 2ms/step
```



Classificação.

```
def predict(model, data, threshold):
  reconstructions = model(data)
  loss = tf.keras.losses.mae(reconstructions, data)
  return tf.math.less(loss, threshold)

def print_stats(predictions, labels):
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  print("Precision = {}".format(precision_score(labels, predictions)))
  print("Recall = {}".format(recall_score(labels, predictions)))
```

Calcule a acurácia para os dois modelos (com camadas densas e convolucionais)

```
print("Dimensões de reconstructions:", reconstructions.shape)
print("Dimensões de data:", data.shape)
data_subset = data[:440, :]

preds = predict(autoencoder, test_data, threshold)
print_stats(preds, test_labels)
```

```
Dimensões de reconstructions: (440, 140)
Dimensões de data: (4998, 140)
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-29-c6bda96bca7b> in <cell line: 6>()
      4
      5 #preds = predict(autoencoder, test_data, threshold)
----> 6 print_stats(preds, test_labels)

NameError: name 'preds' is not defined
```

PESQUISAR NO STACK OVERFLOW

Parte III: Redes Generativas Adversariais (40pt)

Leia o tutorial sobre a pix2pix em Tensofrflow Tutorials. O pix2pix foi apresentado em Image-to-image translation with conditional adversarial networks by Isola et al. (2017) e se trata de uma rede generativa adversarial condicional para geração de fachadas de prédios condicionada a uma máscara reprtesentando a arquitetura. baixe o noterbook do tutorial, estude e treine a GAN. Após o treinamento, construa você mesmo 3 máscaras (usando algum software de desenho) e faça uma inferência com a rede. Anexe no notebook a máscara e sua respectiva saída.

ToDo : Fachadas de prédios (40pt)

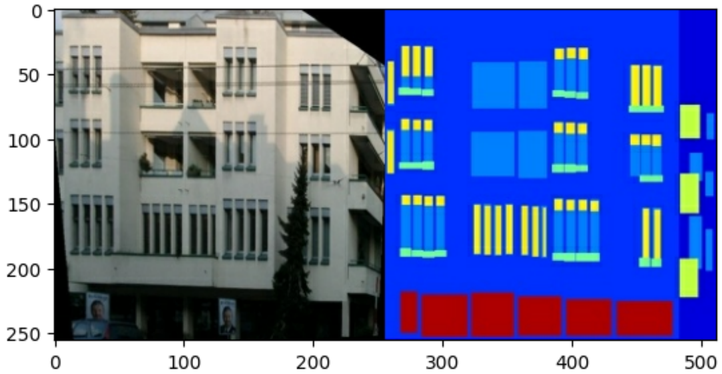
```
# ToDO : Criar 3 máscaras e gerar 3 saídas com a pix2pix para o problema de fachadas de prédios.

#Importar TensorFlow e outras bibliotecas
import tensorflow as tf
```

```
import os
import pathlib
import time
import datetime

from matplotlib import pyplot as plt
from IPython import display
```

Carregar o conjunto de dados

```
dataset_name = "facades"

_URL = f'http://efrosgans.eecs.berkeley.edu/pix2pix/datasets/{dataset_name}.tar.gz'

path_to_zip = tf.keras.utils.get_file(
    fname=f"{dataset_name}.tar.gz",
    origin=_URL,
    extract=True)

path_to_zip  = pathlib.Path(path_to_zip)

PATH = path_to_zip.parent/dataset_name

list(PATH.parent.iterdir())

sample_image = tf.io.read_file(str(PATH / 'train/1.jpg'))
sample_image = tf.io.decode_jpeg(sample_image)
print(sample_image.shape)

plt.figure()
plt.imshow(sample_image)
```

```
Downloading data from http://efrosgans.eecs.berkeley.edu/pix2pix/datasets/facades.tar
30168306/30168306 [==============================] - 10s 0us/step
(256, 512, 3)
<matplotlib.image.AxesImage at 0x7b985e537ca0>
```



Defina uma função que carrega arquivos de imagem e gera dois tensores de imagem:

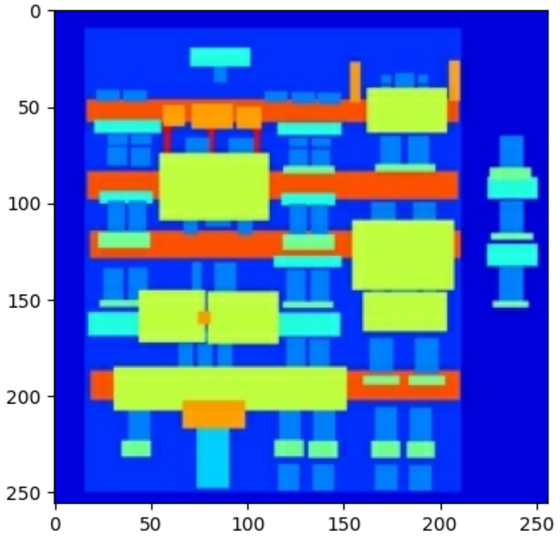
```
def load(image_file):
  # Read and decode an image file to a uint8 tensor
  image = tf.io.read_file(image_file)
  image = tf.io.decode_jpeg(image)

  # Split each image tensor into two tensors:
  # - one with a real building facade image
  # - one with an architecture label image
  w = tf.shape(image)[1]
  w = w // 2
  input_image = image[:, w:, :]
  real_image = image[:, :w, :]

  # Convert both images to float32 tensors
  input_image = tf.cast(input_image, tf.float32)
  real_image = tf.cast(real_image, tf.float32)

  return input_image, real_image
```

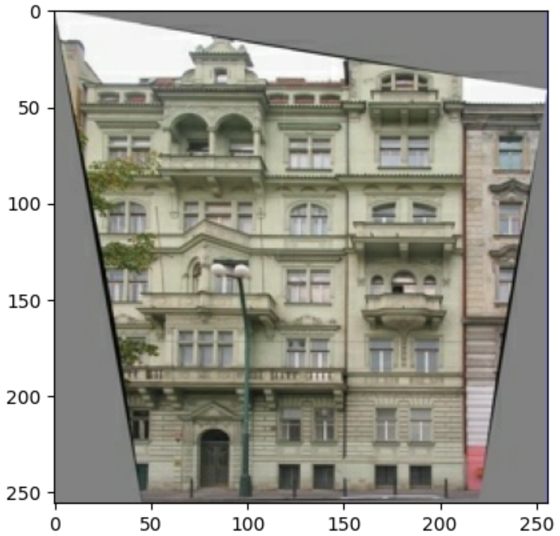
plotando imagem

```
inp, re = load(str(PATH / 'train/100.jpg'))
# Casting to int for matplotlib to display the images
```

```
plt.figure()
plt.imshow(inp / 255.0)
plt.figure()
plt.imshow(re / 255.0)
```

```
<matplotlib.image.AxesImage at 0x7b98503c9600>
```





Clique duas vezes (ou pressione "Enter") para editar

```
# The facade training set consist of 400 images
BUFFER_SIZE = 400
# The batch size of 1 produced better results for the U-Net in the original pix2pix experiment
BATCH_SIZE = 1
# Each image is 256x256 in size
IMG_WIDTH = 256
IMG_HEIGHT = 256
```

Clique duas vezes (ou pressione "Enter") para editar

```
def resize(input_image, real_image, height, width):
  input_image = tf.image.resize(input_image, [height, width],
                              method=tf.image.ResizeMethod.NEAREST_NEIGHBOR)
  real_image = tf.image.resize(real_image, [height, width],
                             method=tf.image.ResizeMethod.NEAREST_NEIGHBOR)

  return input_image, real_image
```

Clique duas vezes (ou pressione "Enter") para editar

```
def random_crop(input_image, real_image):
  stacked_image = tf.stack([input_image, real_image], axis=0)
  cropped_image = tf.image.random_crop(
      stacked_image, size=[2, IMG_HEIGHT, IMG_WIDTH, 3])

  return cropped_image[0], cropped_image[1]
```

Clique duas vezes (ou pressione "Enter") para editar

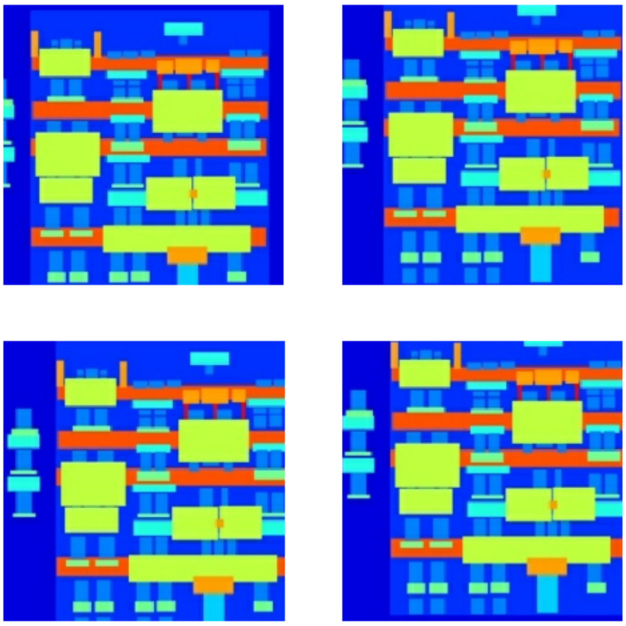
```
# Normalizing the images to [-1, 1]
def normalize(input_image, real_image):
  input_image = (input_image / 127.5) - 1
  real_image = (real_image / 127.5) - 1

  return input_image, real_image
```

Clique duas vezes (ou pressione "Enter") para editar

```
@tf.function()
def random_jitter(input_image, real_image):
  # Resizing to 286x286
  input_image, real_image = resize(input_image, real_image, 286, 286)

  # Random cropping back to 256x256
  input_image, real_image = random_crop(input_image, real_image)

  if tf.random.uniform(()) > 0.5:
    # Random mirroring
    input_image = tf.image.flip_left_right(input_image)
    real_image = tf.image.flip_left_right(real_image)

  return input_image, real_image
```

Clique duas vezes (ou pressione "Enter") para editar

```
plt.figure(figsize=(6, 6))
for i in range(4):
  rj_inp, rj_re = random_jitter(inp, re)
  plt.subplot(2, 2, i + 1)
  plt.imshow(rj_inp / 255.0)
  plt.axis('off')
plt.show()
```



Clique duas vezes (ou pressione "Enter") para editar

```
def load_image_train(image_file):
  input_image, real_image = load(image_file)
  input_image, real_image = random_jitter(input_image, real_image)
  input_image, real_image = normalize(input_image, real_image)

  return input_image, real_image
```

Clique duas vezes (ou pressione "Enter") para editar

```
def load_image_test(image_file):
  input_image, real_image = load(image_file)
  input_image, real_image = resize(input_image, real_image,
                                   IMG_HEIGHT, IMG_WIDTH)
  input_image, real_image = normalize(input_image, real_image)

  return input_image, real_image
```

Clique duas vezes (ou pressione "Enter") para editar

```
train_dataset = tf.data.Dataset.list_files(str(PATH / 'train/*.jpg'))
train_dataset = train_dataset.map(load_image_train,
                                  num_parallel_calls=tf.data.AUTOTUNE)
train_dataset = train_dataset.shuffle(BUFFER_SIZE)
train_dataset = train_dataset.batch(BATCH_SIZE)
```

Clique duas vezes (ou pressione "Enter") para editar

```
try:
  test_dataset = tf.data.Dataset.list_files(str(PATH / 'test/*.jpg'))
except tf.errors.InvalidArgumentError:
  test_dataset = tf.data.Dataset.list_files(str(PATH / 'val/*.jpg'))
test_dataset = test_dataset.map(load_image_test)
test_dataset = test_dataset.batch(BATCH_SIZE)
```

```
OUTPUT_CHANNELS = 3
```

```
def downsample(filters, size, apply_batchnorm=True):
  initializer = tf.random_normal_initializer(0., 0.02)

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

  if apply_batchnorm:
    result.add(tf.keras.layers.BatchNormalization())

  result.add(tf.keras.layers.LeakyReLU())

  return result
```

```
down_model = downsample(3, 4)
down_result = down_model(tf.expand_dims(inp, 0))
print (down_result.shape)
```

```
(1, 128, 128, 3)
```

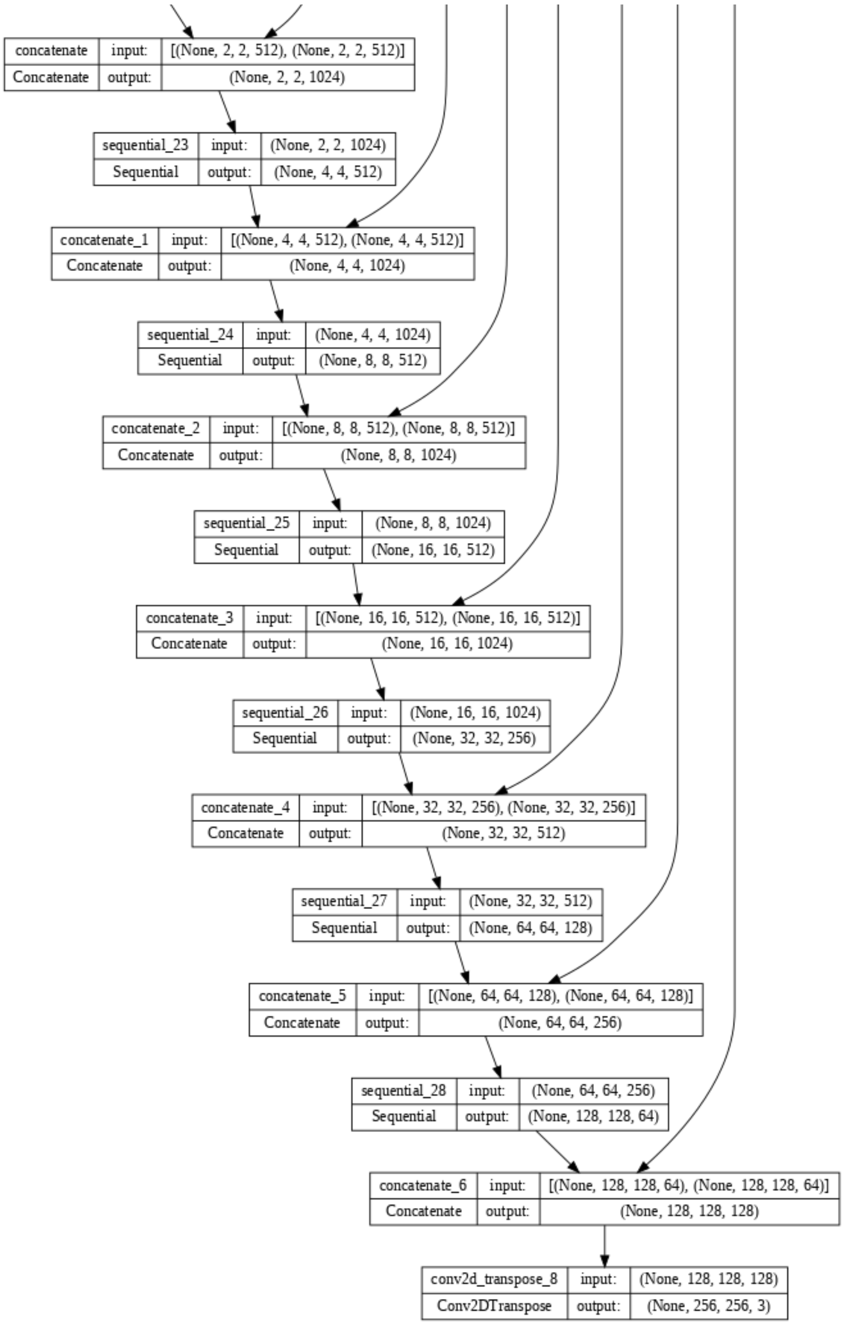
```
def upsample(filters, size, apply_dropout=False):
  initializer = tf.random_normal_initializer(0., 0.02)

  result = tf.keras.Sequential()
  result.add(
    tf.keras.layers.Conv2DTranspose(filters, size, strides=2,
                                    padding='same',
                                    kernel_initializer=initializer,
                                    use_bias=False))

  result.add(tf.keras.layers.BatchNormalization())

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

  result.add(tf.keras.layers.ReLU())

  return result
```

```
up_model = upsample(3, 4)
up_result = up_model(down_result)
print (up_result.shape)
```

```
(1, 256, 256, 3)
```

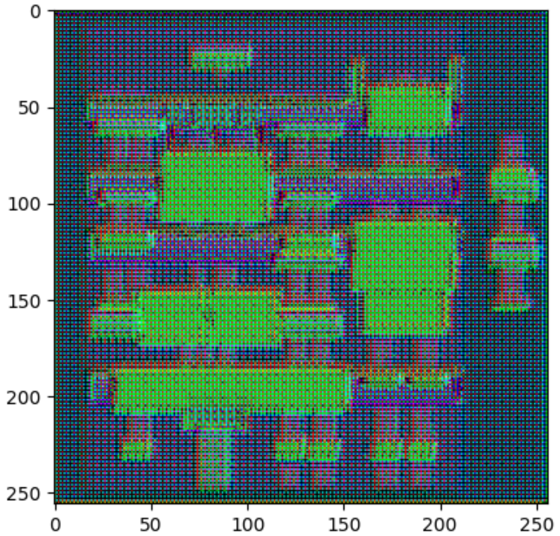
```
def Generator():
  inputs = tf.keras.layers.Input(shape=[256, 256, 3])

  down_stack = [
    downsample(64, 4, apply_batchnorm=False),  # (batch_size, 128, 128, 64)
    downsample(128, 4),  # (batch_size, 64, 64, 128)
    downsample(256, 4),  # (batch_size, 32, 32, 256)
    downsample(512, 4),  # (batch_size, 16, 16, 512)
    downsample(512, 4),  # (batch_size, 8, 8, 512)
    downsample(512, 4),  # (batch_size, 4, 4, 512)
    downsample(512, 4),  # (batch_size, 2, 2, 512)
    downsample(512, 4),  # (batch_size, 1, 1, 512)
  ]

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

  initializer = tf.random_normal_initializer(0., 0.02)
  last = tf.keras.layers.Conv2DTranspose(OUTPUT_CHANNELS, 4,
                                         strides=2,
                                         padding='same',
                                         kernel_initializer=initializer,
                                         activation='tanh')  # (batch_size, 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 = tf.keras.layers.Concatenate()([x, skip])

  x = last(x)

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

```
generator = Generator()
tf.keras.utils.plot_model(generator, show_shapes=True, dpi=64)
```


concatenate | input: | [(None, 2, 2, 512), (None, 2, 2, 512)]
Concatenate | output: | (None, 2, 2, 1024)
sequential_23 | input: | (None, 2, 2, 1024)
Sequential | output: | (None, 4, 4, 512)
concatenate_1 | input: | [(None, 4, 4, 512), (None, 4, 4, 512)]
Concatenate | output: | (None, 4, 4, 1024)
sequential_24 | input: | (None, 4, 4, 1024)
Sequential | output: | (None, 8, 8, 512)
concatenate_2 | input: | [(None, 8, 8, 512), (None, 8, 8, 512)]
Concatenate | output: | (None, 8, 8, 1024)
sequential_25 | input: | (None, 8, 8, 1024)
Sequential | output: | (None, 16, 16, 512)
concatenate_3 | input: | [(None, 16, 16, 512), (None, 16, 16, 512)]
Concatenate | output: | (None, 16, 16, 1024)
sequential_26 | input: | (None, 16, 16, 1024)
Sequential | output: | (None, 32, 32, 256)
concatenate_4 | input: | [(None, 32, 32, 256), (None, 32, 32, 256)]
Concatenate | output: | (None, 32, 32, 512)
sequential_27 | input: | (None, 32, 32, 512)
Sequential | output: | (None, 64, 64, 128)
concatenate_5 | input: | [(None, 64, 64, 128), (None, 64, 64, 128)]
Concatenate | output: | (None, 64, 64, 256)
sequential_28 | input: | (None, 64, 64, 256)
Sequential | output: | (None, 128, 128, 64)
concatenate_6 | input: | [(None, 128, 128, 64), (None, 128, 128, 64)]
Concatenate | output: | (None, 128, 128, 128)
conv2d_transpose_8 | input: | (None, 128, 128, 128)
Conv2DTranspose | output: | (None, 256, 256, 3)

```
gen_output = generator(inp[tf.newaxis, ...], training=False)
plt.imshow(gen_output[0, ...])
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB d
<matplotlib.image.AxesImage at 0x7b9832e89390>
```



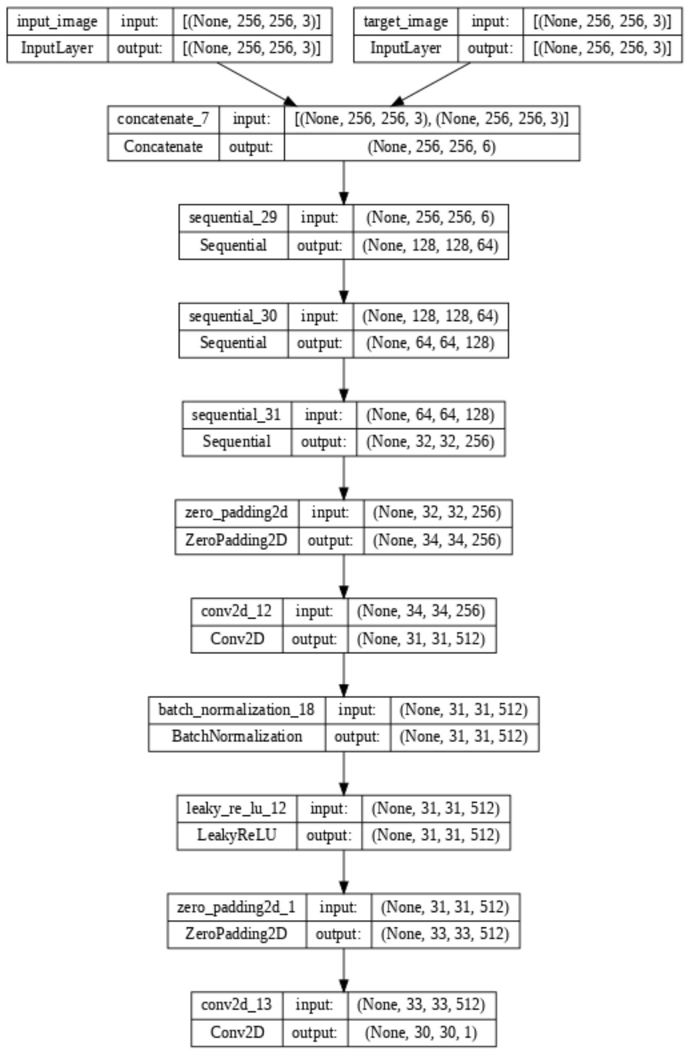

```
LAMBDA = 100
```

```
loss_object = tf.keras.losses.BinaryCrossentropy(from_logits=True)
```

```
def generator_loss(disc_generated_output, gen_output, target):
  gan_loss = loss_object(tf.ones_like(disc_generated_output), disc_generated_output)

  # Mean absolute error
  l1_loss = tf.reduce_mean(tf.abs(target - gen_output))

  total_gen_loss = gan_loss + (LAMBDA * l1_loss)

  return total_gen_loss, gan_loss, l1_loss
```

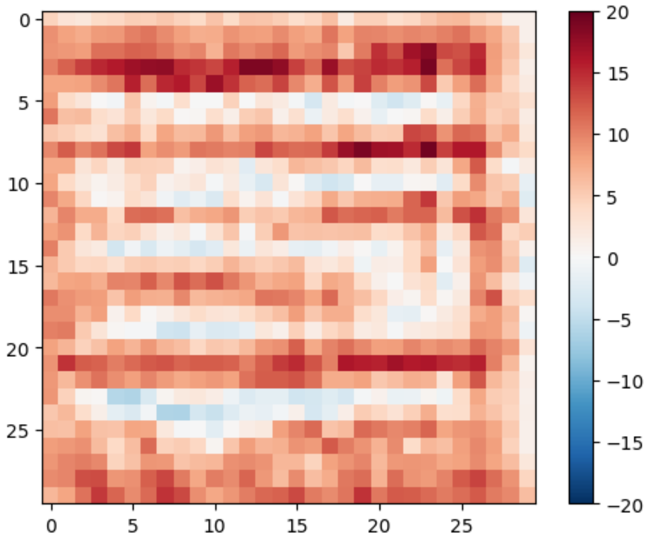
```
def Discriminator():
  initializer = tf.random_normal_initializer(0., 0.02)

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

  x = tf.keras.layers.concatenate([inp, tar])  # (batch_size, 256, 256, channels*2)

  down1 = downsample(64, 4, False)(x)  # (batch_size, 128, 128, 64)
  down2 = downsample(128, 4)(down1)  # (batch_size, 64, 64, 128)
  down3 = downsample(256, 4)(down2)  # (batch_size, 32, 32, 256)

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

  batchnorm1 = tf.keras.layers.BatchNormalization()(conv)

  leaky_relu = tf.keras.layers.LeakyReLU()(batchnorm1)

  zero_pad2 = tf.keras.layers.ZeroPadding2D()(leaky_relu)  # (batch_size, 33, 33, 512)

  last = tf.keras.layers.Conv2D(1, 4, strides=1,
                                kernel_initializer=initializer)(zero_pad2)  # (batch_size, 30, 30, 1)

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

```
discriminator = Discriminator()
tf.keras.utils.plot_model(discriminator, show_shapes=True, dpi=64)
```




```
disc_out = discriminator([inp[tf.newaxis, ...], gen_output], training=False)
plt.imshow(disc_out[0, ..., -1], vmin=-20, vmax=20, cmap='RdBu_r')
plt.colorbar()
```

```
<matplotlib.colorbar.Colorbar at 0x7b9832ef6410>
```




```
def discriminator_loss(disc_real_output, disc_generated_output):
  real_loss = loss_object(tf.ones_like(disc_real_output), disc_real_output)

  generated_loss = loss_object(tf.zeros_like(disc_generated_output), disc_generated_output)

  total_disc_loss = real_loss + generated_loss

  return total_disc_loss
```

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

```
checkpoint_dir = './training_checkpoints'
checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optimizer,
                                 generator=generator,
                                 discriminator=discriminator)
```

```
def generate_images(model, test_input, tar):
  prediction = model(test_input, training=True)
  plt.figure(figsize=(15, 15))

  display_list = [test_input[0], tar[0], prediction[0]]
  title = ['Input Image', 'Ground Truth', 'Predicted Image']

  for i in range(3):
    plt.subplot(1, 3, i+1)
    plt.title(title[i])
    # Getting the pixel values in the [0, 1] range to plot.
    plt.imshow(display_list[i] * 0.5 + 0.5)
    plt.axis('off')
  plt.show()
```

```
for example_input, example_target in test_dataset.take(1):
  generate_images(generator, example_input, example_target)
```