Trabalho 1 - Autoencoder variacional

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Dataset

Os dados foram retirados do repositorio https://drive.google.com/file/d/1HG7YnakUkjaxtNMclbl2t5sJwGLcHYsI/view?usp=sharing, que sao imagens de rostos de animes.

Resultado de um scrape, devidamente documentado no github https://github.com/bchao1/Anime-Face-Dataset

Para consumir as imagens, basta fazer o download do arquivo zip e aloca-las no google drive.

Importando bibliotecas

```
# Images
from os import listdir
from matplotlib import image
from PIL import Image
import numpy as np

# Keras
import tensorflow.keras.backend as K
from tensorflow.keras import layers
import tensorflow as tf
from tensorflow.keras.models import Model,Sequential
```

Lendo as Images

As imagens inicialmente zipadas, serao lidas na sessao do colab

```
# load all images in a directory
loaded_images = list()
images_path = 'E:\\Coisas\\Notas4\\modelos_generativos\\cropped\\'
for filename in listdir(images_path):
    try:
        # load image
        img_data = Image.open(images_path+ filename)
        # store loaded image
        loaded_images.append(np.array(img_data.resize((32,32))))

loaded_images = np.asarray(loaded_images)
```

```
loaded_images.shape
```

```
(63569, 32, 32, 3)
```

Normalizando as Images

Normalizar os dados, de maneira que fiquem entre 0 e 1.

zi=xi−min(x) / max(x)−min(x)

```
loaded_images = (loaded_images - np.min(loaded_images)) / (np.max(loaded_images) - np.min(loaded_images))
```

Configurando o Amostrador

```
# Classe de camada do amsotrador
class Sampling(layers.Layer):
    # Método para inicializar classe
    def __init__(self):
        # Inicializa classe
        super(Sampling, self).__init__()

    # Método para realizar cálculos na camada do amsotrador
    def call(self, inputs):
        """Dados de entrada:
        Vetor de médias: z_mean;
        Logaritmo do vetor de variâncias: z_log_var"""

        # Separa média e desvio padrão da entrada na forma de lista
        z_mean, z_log_var = inputs

        # Recupera dimensões dos tensores de média e desvio padrão
        batch = tf.shape(z_mean)[0]
        dim = tf.shape(z_mean)[1]

        # Gera número aleatório com distribuição Gaussiana de média 0 e desvio padrão 1
        alfa = K.random_normal(shape=(batch, dim))

        # Retorna vetor de código amostrado
        return z_mean + tf.exp(0.5 * z_log_var) * alfa
```

Configurando o Codificador

```
shape = loaded_images.shape[1:4]
encoder_input = layers.Input(shape)

x = layers.Conv2D(32, kernel_size=3, strides=2, padding='same', activation=layers.LeakyReLU())(encoder_in
x = layers.Conv2D(32, kernel_size=3, strides=2, padding='same', activation=layers.LeakyReLU())(x)
x = layers.Conv2D(32, kernel_size=3, strides=2, padding='same', activation=layers.LeakyReLU())(x)
x = layers.BatchNormalization()(x)

conv_shape = K.int_shape(x)
```

```
x = layers.Flatten()(x)

latent_dim = 2
z_mean = layers.Dense(latent_dim, name="z_mean")(x)
z_log_var = layers.Dense(latent_dim, name="z_log_var")(x)

z = Sampling()([z_mean, z_log_var])

encoder = Model(encoder_input, [z_mean, z_log_var, z], name="encoder")
print(encoder.summary())
```

```
Model: "encoder"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 32, 32, 3)]  0
__________________________________________________________________________________________________
conv2d (Conv2D)                 (None, 16, 16, 32)   896         input_1[0][0]
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 8, 8, 32)     9248        conv2d[0][0]
__________________________________________________________________________________________________
conv2d_2 (Conv2D)               (None, 4, 4, 32)     9248        conv2d_1[0][0]
__________________________________________________________________________________________________
batch_normalization (BatchNorma (None, 4, 4, 32)     128         conv2d_2[0][0]
__________________________________________________________________________________________________
flatten (Flatten)               (None, 512)          0           batch_normalization|
__________________________________________________________________________________________________
z_mean (Dense)                  (None, 2)            1026        flatten[0][0]
__________________________________________________________________________________________________
z_log_var (Dense)               (None, 2)            1026        flatten[0][0]
__________________________________________________________________________________________________
sampling (Sampling)             (None, 2)            0           z_mean[0][0]
                                                                 z_log_var[0][0]
==================================================================================================
Total params: 21,572
Trainable params: 21,508
Non-trainable params: 64
__________________________________________________________________________________________________
None
```

Configurando o Decodificador

```
decoder_input  = layers.Input(shape=(latent_dim,))
decoder = layers.Dense(conv_shape[1]*conv_shape[2]*conv_shape[3], activation='relu')(decoder_input)
decoder = layers.Reshape((conv_shape[1], conv_shape[2], conv_shape[3]))(decoder)
decoder_conv = layers.Conv2DTranspose(32, kernel_size=3, strides=2, padding='same', activation='relu')(de
decoder_conv = layers.Conv2DTranspose(16, kernel_size=3, strides=2, padding='same', activation='relu')(de
decoder_conv = layers.Conv2DTranspose(8, kernel_size=3, strides=2, padding='same', activation='relu')(dec
decoder_outputs = layers.Conv2D(3, kernel_size=1, strides=1, padding='same', activation='sigmoid')(decode

decoder = Model(decoder_input, decoder_outputs, name="decoder")
decoder.summary()
```

```
Model: "decoder"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
input_2 (InputLayer)         [(None, 2)]               0
_________________________________________________________________
dense (Dense)                (None, 512)               1536
_________________________________________________________________
reshape (Reshape)            (None, 4, 4, 32)          0
_________________________________________________________________
conv2d_transpose (Conv2DTran (None, 8, 8, 32)          9248
_________________________________________________________________
conv2d_transpose_1 (Conv2DTr (None, 16, 16, 16)        4624
_________________________________________________________________
conv2d_transpose_2 (Conv2DTr (None, 32, 32, 8)         1160
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 3)         27
=================================================================
Total params: 16,595
Trainable params: 16,595
Non-trainable params: 0
_________________________________________________________________
```

Termo de Regularizacao KL da Funcao de Custo

```
# Termo de regularização KL
def KL_loss(z_mean, z_log_var):
    # calcula desvio padrão
    sigma = tf.exp(0.5 * z_log_var)

    # Calcula custo KL
    kl_loss = 0.5*(sigma**2 + z_mean**2 - z_log_var - 1.0)

    # Calcula média do resultado
    kl_loss = tf.reduce_mean(tf.reduce_sum(kl_loss, axis=1))

    return kl_loss
```

Autoencoder completo

```
# define fator de regularização
beta = 1/(32*32)

# Camada de entrada
inputs = layers.Input(shape=(shape))

# Inclui codificador
z_mean, z_log_var, z = encoder(inputs)

# Incluir decodificador
decoder_output = decoder(z)

# Instância AEV
AEV = Model(inputs, decoder_output)

# Define termo de regularização KL
loss = beta*KL_loss(z_mean, z_log_var)
```

```
# Adiciona termo de regularização KL omo função de custo adicional
AEV.add_loss(loss)

# Summario do AEV
AEV.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 32, 32, 3)]  0
__________________________________________________________________________________________________
encoder (Functional)            [(None, 2), (None, 2 21572       input_3[0][0]
__________________________________________________________________________________________________
decoder (Functional)            (None, 32, 32, 3)    16595       encoder[0][2]
__________________________________________________________________________________________________
tf.math.multiply (TFOpLambda)   (None, 2)            0           encoder[0][1]
__________________________________________________________________________________________________
tf.math.exp (TFOpLambda)        (None, 2)            0           tf.math.multiply[0]|
__________________________________________________________________________________________________
tf.math.pow (TFOpLambda)        (None, 2)            0           tf.math.exp[0][0]
__________________________________________________________________________________________________
tf.math.pow_1 (TFOpLambda)      (None, 2)            0           encoder[0][0]
__________________________________________________________________________________________________
tf.__operators__.add (TFOpLambd (None, 2)            0           tf.math.pow[0][0]
                                                                 tf.math.pow_1[0][0]
__________________________________________________________________________________________________
tf.math.subtract (TFOpLambda)   (None, 2)            0           tf.__operators__.ad
                                                                 encoder[0][1]
__________________________________________________________________________________________________
tf.math.subtract_1 (TFOpLambda) (None, 2)            0           tf.math.subtract[0]|
__________________________________________________________________________________________________
tf.math.multiply_1 (TFOpLambda) (None, 2)            0           tf.math.subtract_1[
__________________________________________________________________________________________________
tf.math.reduce_sum (TFOpLambda) (None,)              0           tf.math.multiply_1[
__________________________________________________________________________________________________
tf.math.reduce_mean (TFOpLambda ()                   0           tf.math.reduce_sum[
__________________________________________________________________________________________________
tf.math.multiply_2 (TFOpLambda) ()                   0           tf.math.reduce_mean|
__________________________________________________________________________________________________
add_loss (AddLoss)              ()                   0           tf.math.multiply_2[
==================================================================================================
Total params: 38,167
Trainable params: 38,103
Non-trainable params: 64
__________________________________________________________________________________________________
```

Compilacao do Autoencoder

```
# Define otimizador Adam
adam = tf.keras.optimizers.Adam(learning_rate=0.001, decay=0.5e-02)

# Compilação do autoencoder
AEV.compile(optimizer=adam, loss='binary_crossentropy', metrics=['binary_accuracy'])
```

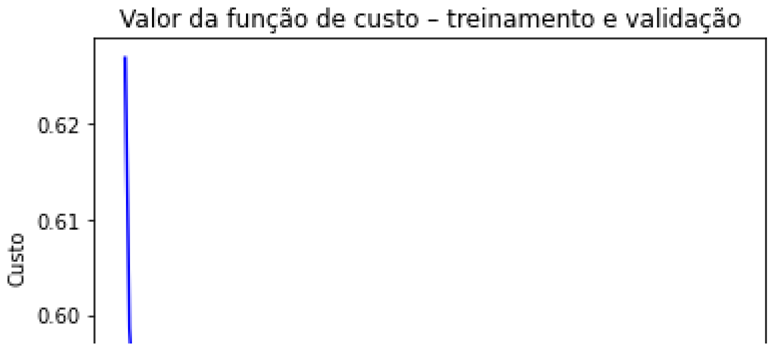
Treinamento do Autoencoder

```
results = AEV.fit(x=loaded_images,
                  y=loaded_images,
                  epochs=150,
                  batch_size=256,
                  shuffle=True)
```

```
Epoch 120/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 121/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 122/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 123/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 124/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 125/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 126/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 127/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 128/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 129/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 130/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 131/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 132/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 133/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 134/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 135/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 136/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 137/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 138/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 139/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 140/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 141/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5856 - binary_ac
Epoch 142/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 143/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 144/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 145/150
```

```
Epoch 145/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 146/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 147/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 148/150
249/249 [==============================] - 4s 16ms/step - loss: 0.5855 - binary_ac
Epoch 149/150
```

```
import matplotlib.pyplot as plt

def plot_train(history):
    history_dict = history.history
    # Salva custos, métricas em vetores
    custo = history_dict['loss']
    acc = history_dict['binary_accuracy']

    # Cria vetor de épocas
    epocas = range(1, len(custo) + 1)

    # Gráfico dos valores de custo
    plt.plot(epocas, custo, 'b', label='Custo - treinamento')
    plt.title('Valor da função de custo – treinamento e validação')
    plt.xlabel('Épocas')
    plt.ylabel('Custo')
    plt.show()

    # Gráfico dos valores da métrica
    plt.plot(epocas, acc, 'b', label='exatidao- treinamento')
    plt.title('Valor da métrica – treinamento e validação')
    plt.xlabel('Épocas')
    plt.ylabel('Exatidao')
    plt.show()

plot_train(results)
```



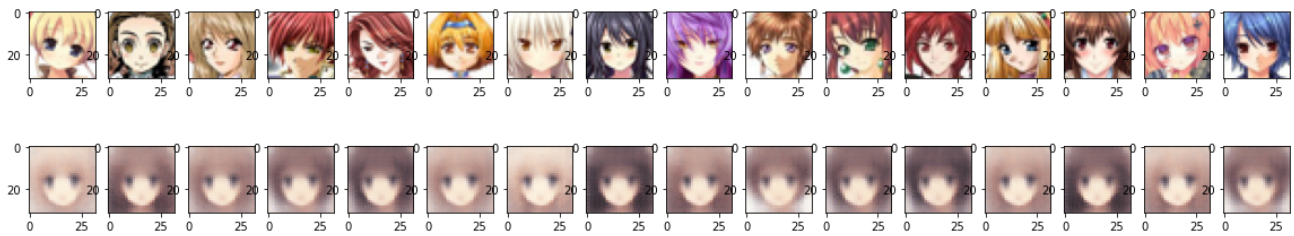
Avaliacao do Autoencoder


```
AEV.evaluate(loaded_images, loaded_images)
```

```
1987/1987 [==============================] - 7s 3ms/step - loss: 0.5855 - binary_accu
[0.5854815244674683, 0.02937604859471321]
```

Comparação das saídas previstas pelo autoencoder com as entradas


```
# Calcula dados reconstriuídos pelo AE
x_prev = 255*AEV.predict(loaded_images)
x_prev = x_prev.astype(int)

#Plot
f, pos = plt.subplots(2, 16, figsize=(20, 4))
for i in range(16):
    pos[0,i].imshow((loaded_images[i]*255).astype(int), cmap='gray')
    pos[1,i].imshow(x_prev[i], interpolation='nearest')
plt.show()
```



```
#erro e metrica para cada uma das images
for i in range(16):
  print(f"imagem numero {i}")
  AEV.evaluate(loaded_images[i:i+1], loaded_images[i:i+1])
```

```
imagem numero 0
1/1 [==============================] - 0s 97ms/step - loss: 0.4906 - binary_accuracy
imagem numero 1
1/1 [==============================] - 0s 15ms/step - loss: 0.6261 - binary_accuracy
imagem numero 2
1/1 [==============================] - 0s 20ms/step - loss: 0.6092 - binary_accuracy
imagem numero 3
1/1 [==============================] - 0s 15ms/step - loss: 0.6423 - binary_accuracy
imagem numero 4
1/1 [==============================] - 0s 14ms/step - loss: 0.6180 - binary_accuracy
imagem numero 5
1/1 [==============================] - 0s 15ms/step - loss: 0.5796 - binary_accuracy
imagem numero 6
1/1 [==============================] - 0s 20ms/step - loss: 0.4674 - binary_accuracy
imagem numero 7
1/1 [==============================] - 0s 18ms/step - loss: 0.6059 - binary_accuracy
imagem numero 8
1/1 [==============================] - 0s 14ms/step - loss: 0.6131 - binary_accuracy
imagem numero 9
1/1 [==============================] - 0s 14ms/step - loss: 0.5749 - binary_accuracy
imagem numero 10
1/1 [==============================] - 0s 16ms/step - loss: 0.6453 - binary_accuracy
imagem numero 11
1/1 [==============================] - 0s 14ms/step - loss: 0.6087 - binary_accuracy
imagem numero 12
1/1 [==============================] - 0s 14ms/step - loss: 0.6094 - binary_accuracy
imagem numero 13
1/1 [==============================] - 0s 13ms/step - loss: 0.5936 - binary_accuracy
imagem numero 14
1/1 [==============================] - 0s 15ms/step - loss: 0.5654 - binary_accuracy
imagem numero 15
1/1 [==============================] - 0s 15ms/step - loss: 0.6248 - binary_accuracy
```

```
AEV.evaluate(loaded_images[1:2], loaded_images[1:2])
```

```
1/1 [==============================] - 0s 14ms/step - loss: 0.6285 - binary_accuracy
[0.6284918785095215, 0.0260416679084301]
```

Geração de novas imagens de dígitos

```
# representações latente geradas aleatóriamente
# Alterar sacle para selecionar dígitos diferentes
scale = 2.
z_rand = np.random.randn(24,latent_dim) + 2.0*scale*(np.random.randint(0, 2, (24, latent_dim)) - 0.5)

# Cria imagem a partir da representação latente
reconst_images_vec = decoder.predict(z_rand)

# Mostra imagens construídas
f, pos = plt.subplots(3, 8, figsize=(18, 8))
for i in range(3):
    for j in range(8):
        index = i*8 + j
        pos[i,j].imshow(np.squeeze(reconst_images_vec[index]), cmap='gray')
        pos[i,j].axes.xaxis.set_visible(False)
```

```
        pos[i,j].axes.yaxis.set_visible(False)
plt.show()
```

Grade de dígitos

```
# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples, n_classes=16):
    # generate points in the latent space
    x_input = np.random.randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    z_input = x_input.reshape(n_samples, latent_dim)
    return z_input

# uniform interpolation between two points in latent space
def interpolate_points(p1, p2, n_steps=8):
    # interpolate ratios between the points
    ratios = np.linspace(0, 1, num=n_steps)
    # linear interpolate vectors
    vectors = list()
    for ratio in ratios:
        v = (1.0 - ratio) * p1 + ratio * p2
        vectors.append(v)
    return np.asarray(vectors)

# create a plot of generated images
def plot_generated(examples, n):
  # plot images
  for i in range(n * n):
    # define subplot
    plt.subplot(n, n, 1 + i)
    # turn off axis
```

```
        plt.axis('off')
        # plot raw pixel data
        plt.imshow(examples[i, :, :])


    plt.show()


# generate points in latent space
n = 20
pts = generate_latent_points(2, n)
# interpolate pairs
results = None
for i in range(0, n, 2):
    # interpolate points in latent space
    interpolated = interpolate_points(pts[i], pts[i+1])
    # generate images
    X = decoder.predict(interpolated)
    # scale from [-1,1] to [0,1]
    X = (X + 1) / 2.0
    if results is None:
        results = X
    else:
        results = np.vstack((results, X))
# plot the result
plot_generated(results, 8)
```

0s conclusão: 18:08