

Training du RNN pour le captioning

Introduction

Afin de mener à bien ce projet nous utilisons un modèle de neurones récurrents, celui-ci aura pour objectif de générer les descriptions textuelles liées à nos images. Les données d'entrées seront issues de nos réseaux convolutionnels. Un modèle de classification pré-entraîné nous permettra d'extraire les features que nous passerons à notre RNN pour la génération de caption.

préparation de l'environnement

```
In [ ]: #imports
import tensorflow as tf

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle

import collections
import random
import re
import numpy as np
import os
import time
import json
from glob import glob
from PIL import Image
import pickle
from tqdm import tqdm

import tensorboard
import datetime

import cv2
```

```
In [ ]: #Setting gpu for limit memory
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    #Restrict Tensorflow to only allocate 6gb of memory on the first GPU
    try:
        tf.config.experimental.set_virtual_device_configuration(gpus[0],
            [tf.config.experimental.VirtualDeviceConfiguration(memory_limit=9144)])
        logical_gpus = tf.config.experimental.list_logical_devices('GPU')
        print(len(gpus), "Physical GPUs,", len(logical_gpus), "Logical GPUs")
    except RuntimeError as e:
        #virtual devices must be set before GPUs have been initialized
        print(e)
```

1 Physical GPUs, 1 Logical GPUs

Chargement des données

```
In [ ]: # Chemin du fichier d'annotations
annotation_folder = "/annotations/"
annotation_file = os.path.abspath('.')+"/annotations/captions_train2014.json"

# Chemin du dossier contenant Les images à annoter
#On va prendre des images pré débruité par Le modele du Livrable 2 pour l'entraî
image_folder = '/denoised_train2014/'
PATH = os.path.abspath('.') + image_folder

# Lecture du fichier d'annotation
with open(annotation_file, 'r') as f:
    annotations = json.load(f)

# Grouper toutes Les annotations ayant Le meme identifiant.
image_path_to_caption = collections.defaultdict(list)
for val in annotations['annotations']:
    # marquer Le debut et La fin de chaque annotation
    caption = '<start> ' + val['caption'] + ' <end>'
    # L'identifiant d'une image fait partie de son chemin d'accès
    image_path = PATH + 'COCO_train2014_' + '%012d.jpg' % (val['image_id'])
    # Rajout du caption associé à image_path
    image_path_to_caption[image_path].append(caption)

# Prendre Les premières images seulement
image_paths = list(image_path_to_caption.keys())
train_image_paths = image_paths[:2000]

# Liste de toutes Les annotations
train_captions = []
# Liste de tous Les noms de fichiers des images dupliquées (en nombre d'annotati
img_name_vector = []

print(len(train_image_paths))

for image_path in train_image_paths:
    caption_list = image_path_to_caption[image_path]
    # Rajout de caption_list dans train_captions
    train_captions.extend(caption_list)
    # Rajout de image_path dupliquée Len(caption_list) fois
    img_name_vector.extend([image_path] * len(caption_list))

print(len(img_name_vector))
```

2000

10005

Débruiteur

On entrera des images débruités dans notre CNN. Pour qu'il s'habitue a des images débruités (on a lancé ce code une fois pour créer un dataset d'image débruitées par le modèle de denoising)

```
In [ ]: # #L2-----
# model_denoising_path = "../Livable_2/best_model/17_4_2024_17h12.keras"
# model_denoising = tf.keras.models.load_model(model_denoising_path)

# #L2
# def prepare_denoising(path):
#     img = cv2.imread(path)
#     img_correct_color = img
#     img_resized = cv2.resize(img_correct_color, (400,400))
#     img_normalized = img_resized.astype('float32') / 255.0
#     img_batch = np.expand_dims(img_normalized, axis=0)
#     return img_batch

In [ ]: # dossier = "denoised_train2014"
# for path in range(img_name_vector):
#     name = img_name_vector[path].split('/')[-1]
#     img = prepare_denoising(path)
#     img = model_denoising.predict(img)

#     cv2.imwrite(f'./{dossier}/{name}', img.squeeze()*255)
```

Préparation d'inceptionV3

Au début, le modèle InceptionV3 est téléchargé sans la couche supérieure (qui est la couche de classification) et avec des poids pré-entraînés sur ImageNet. Une nouvelle couche d'entrée est créée avec la forme (299,299,3), qui est la forme d'entrée attendue par InceptionV3. La dernière couche cachée du modèle, qui contient la représentation compacte de l'image, est récupérée. Un nouveau modèle, `image_features_extract_model`, est ensuite créé avec la nouvelle entrée et la dernière couche cachée du modèle InceptionV3.

Ensuite, une fonction `load_image` est définie. Cette fonction prend un chemin d'image en entrée et renvoie un tuple contenant l'image traitée et son chemin. Les étapes de traitement de l'image comprennent le chargement du fichier image, le décodage de l'image en RGB, le redimensionnement de l'image à (299, 299), et la normalisation des pixels de l'image entre -1 et 1 en utilisant la fonction `preprocess_input` de InceptionV3.

Nous procédons ensuite au prétraitement des images. Il obtient d'abord les noms uniques des images de `img_name_vector` et les trie. Un jeu de données TensorFlow est créé à partir de ces noms d'images. La fonction `load_image` est ensuite appliquée à ce jeu de données en parallèle, et le jeu de données est divisé en lots de 16.

Nous itérons ensuite sur chaque lot du jeu de données. Pour chaque lot, le `image_features_extract_model` est utilisé pour calculer les caractéristiques des images. Les caractéristiques sont ensuite remodelées de (16,8,8,2048) à (16,64,2048). Pour chaque image du lot, le chemin de l'image et les caractéristiques sont sauvegardés dans un fichier en utilisant `numpy.save`. Le chemin du fichier est le même que le chemin de l'image, et les caractéristiques sont sauvegardées dans le format binaire numpy. Ce processus est répété pour tous les lots dans le jeu de données.

```
In [ ]: # Telechargement du modèle InceptionV3 pré-entraîné avec La classification sur Im
image_model = tf.keras.applications.InceptionV3(include_top=False,
                                                weights='imagenet')

# Creation d'une variable qui sera l'entrée du nouveau modèle de pre-traitement
new_input = image_model.input
# récupérer la dernière couche caché qui contient l'image en representation comp
hidden_layer = image_model.layers[-1].output

# Modèle qui calcule une representation dense des images avec InceptionV3
image_features_extract_model = tf.keras.Model(new_input, hidden_layer)
image_features_extract_model.summary()

# Définition de La fonction load_image
def load_image(image_path):
    """
    La fonction load_image a pour entrée le chemin d'une image et pour sortie un
    contenant l'image traitée ainsi que son chemin d'accès.
    La fonction load_image effectue les traitement suivant:
        1. Chargement du fichier correspondant au chemin d'accès image_path
        2. Décodage de l'image en RGB.
        3. Redimensionnement de l'image en taille (299, 299).
        4. Normalisation des pixels de l'image entre -1 et 1
    """
    img = tf.io.read_file(image_path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, (299, 299))
    img = tf.keras.applications.inception_v3.preprocess_input(img)
    return img, image_path

# Pré-traitement des images
# Prendre Les noms des images
encode_train = sorted(set(img_name_vector))

# Creation d'une instance de "tf.data.Dataset" partant des noms des images
image_dataset = tf.data.Dataset.from_tensor_slices(encode_train)
# Division du données en batchs après application du pré-traitement fait par Lo
image_dataset = image_dataset.map(
    load_image, num_parallel_calls=tf.data.experimental.AUTOTUNE).batch(16)

# Parcourir Le dataset batch par batch pour effectuez Le pre-traitement d'Incept
print(image_dataset)
for img, path in tqdm(image_dataset):
    # Pré-traitement du batch (de taille (16,8,8,2048)) courant par InceptionV3
    batch_features = image_features_extract_model(img)
    # Resize du batch de taille (16,8,8,2048) en taille (16,64,2048)
    batch_features = tf.reshape(batch_features,
                                (batch_features.shape[0], -1, batch_features.shape[1],
                                 batch_features.shape[2], batch_features.shape[3]))
    # Parcourir Le batch courant et stocker Le chemin ainsi que Le batch avec np
    for bf, p in zip(batch_features, path):
        path_of_feature = p.numpy().decode("utf-8")
        # (chemin de l'image associe a sa nouvelle representation , representati
        np.save(path_of_feature, bf.numpy())
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, None, None, 3)]	0	[]
conv2d (Conv2D)	(None, None, None, 32)	864	['input_1[0]']
batch_normalization (BatchNormalization)	(None, None, None, 32)	96	['conv2d[0][0]']
activation (Activation)	(None, None, None, 32)	0	['batch_normalization[0][0]']
conv2d_1 (Conv2D)	(None, None, None, 32)	9216	['activation[0]']
batch_normalization_1 (BatchNormalization)	(None, None, None, 32)	96	['conv2d_1[0]']
activation_1 (Activation)	(None, None, None, 32)	0	['batch_normalization_1[0][0]']
conv2d_2 (Conv2D)	(None, None, None, 64)	18432	['activation_1[0][0]']
batch_normalization_2 (BatchNormalization)	(None, None, None, 64)	192	['conv2d_2[0]']
activation_2 (Activation)	(None, None, None, 64)	0	['batch_normalization_2[0][0]']
max_pooling2d (MaxPooling2D)	(None, None, None, 64)	0	['activation_2[0][0]']
conv2d_3 (Conv2D)	(None, None, None, 80)	5120	['max_pooling2d[0][0]']
batch_normalization_3 (BatchNormalization)	(None, None, None, 80)	240	['conv2d_3[0]']
activation_3 (Activation)	(None, None, None, 80)	0	['batch_normalization_3[0][0]']

conv2d_4 (Conv2D) [0][0]']	(None, None, None, 192)	138240	['activation_3
batch_normalization_4 (Batch Normalization) [0]']	(None, None, None, 192)	576	['conv2d_4[0]
activation_4 (Activation) ation_4[0][0]']	(None, None, None, 192)	0	['batch_normaliz
max_pooling2d_1 (MaxPooling2D) [0][0]']	(None, None, None, 192)	0	['activation_4
conv2d_8 (Conv2D) 1[0][0]']	(None, None, None, 64)	12288	['max_pooling2d_
batch_normalization_8 (Batch Normalization) [0]']	(None, None, None, 64)	192	['conv2d_8[0]
activation_8 (Activation) ation_8[0][0]']	(None, None, None, 64)	0	['batch_normaliz
conv2d_6 (Conv2D) 1[0][0]']	(None, None, None, 48)	9216	['max_pooling2d_
conv2d_9 (Conv2D) [0][0]']	(None, None, None, 96)	55296	['activation_8
batch_normalization_6 (Batch Normalization) [0]']	(None, None, None, 48)	144	['conv2d_6[0]
batch_normalization_9 (Batch Normalization) [0]']	(None, None, None, 96)	288	['conv2d_9[0]
activation_6 (Activation) ation_6[0][0]']	(None, None, None, 48)	0	['batch_normaliz
activation_9 (Activation) ation_9[0][0]']	(None, None, None, 96)	0	['batch_normaliz
average_pooling2d (AveragePooling2D) 1[0][0]']	(None, None, None, 192)	0	['max_pooling2d_
conv2d_5 (Conv2D) 1[0][0]']	(None, None, None, 64)	12288	['max_pooling2d_

conv2d_7 (Conv2D) [0][0]'	(None, None, None, 64)	76800	['activation_6
conv2d_10 (Conv2D) [0][0]'	(None, None, None, 96)	82944	['activation_9
conv2d_11 (Conv2D) g2d[0][0]'	(None, None, None, 32)	6144	['average_poolin
batch_normalization_5 (BatchNo [0]') rmalization)	(None, None, None, 64)	192	['conv2d_5[0]
batch_normalization_7 (BatchNo [0]') rmalization)	(None, None, None, 64)	192	['conv2d_7[0]
batch_normalization_10 (BatchN [0]') ormalization)	(None, None, None, 96)	288	['conv2d_10[0]
batch_normalization_11 (BatchN [0]') ormalization)	(None, None, None, 32)	96	['conv2d_11[0]
activation_5 (Activation) ation_5[0][0]'	(None, None, None, 64)	0	['batch_normaliz
activation_7 (Activation) ation_7[0][0]'	(None, None, None, 64)	0	['batch_normaliz
activation_10 (Activation) ation_10[0][0]'	(None, None, None, 96)	0	['batch_normaliz
activation_11 (Activation) ation_11[0][0]'	(None, None, None, 32)	0	['batch_normaliz
mixed0 (Concatenate) [0][0]', [0][0]', [0][0]', [0][0]'	(None, None, None, 256)	0	['activation_5 'activation_7 'activation_10 'activation_11
conv2d_15 (Conv2D)	(None, None, None, 64)	16384	['mixed0[0][0]']
batch_normalization_15 (BatchN [0]') ormalization)	(None, None, None, 64)	192	['conv2d_15[0]

activation_15 (Activation) activation_15[0][0]'	(None, None, None, 64)	0	['batch_normaliz
conv2d_13 (Conv2D)	(None, None, None, 48)	12288	['mixed0[0][0]']
conv2d_16 (Conv2D) [0][0]'	(None, None, None, 96)	55296	['activation_15
batch_normalization_13 (BatchN [0]') ormalization)	(None, None, None, 48)	144	['conv2d_13[0]
batch_normalization_16 (BatchN [0]') ormalization)	(None, None, None, 96)	288	['conv2d_16[0]
activation_13 (Activation) ation_13[0][0]'	(None, None, None, 48)	0	['batch_normaliz
activation_16 (Activation) ation_16[0][0]'	(None, None, None, 96)	0	['batch_normaliz
average_pooling2d_1 (AveragePo oling2D)	(None, None, None, 256)	0	['mixed0[0][0]']
conv2d_12 (Conv2D)	(None, None, None, 64)	16384	['mixed0[0][0]']
conv2d_14 (Conv2D) [0][0]'	(None, None, None, 64)	76800	['activation_13
conv2d_17 (Conv2D) [0][0]'	(None, None, None, 96)	82944	['activation_16
conv2d_18 (Conv2D) g2d_1[0][0]'	(None, None, None, 64)	16384	['average_poolin
batch_normalization_12 (BatchN [0]') ormalization)	(None, None, None, 64)	192	['conv2d_12[0]
batch_normalization_14 (BatchN [0]') ormalization)	(None, None, None, 64)	192	['conv2d_14[0]
batch_normalization_17 (BatchN [0]') ormalization)	(None, None, None, 96)	288	['conv2d_17[0]
batch_normalization_18 (BatchN [0]') ormalization)	(None, None, None, 64)	192	['conv2d_18[0]

activation_12 (Activation) activation_12[0][0]'	(None, None, None, 64)	0	['batch_normaliz
activation_14 (Activation) activation_14[0][0]'	(None, None, None, 64)	0	['batch_normaliz
activation_17 (Activation) activation_17[0][0]'	(None, None, None, 96)	0	['batch_normaliz
activation_18 (Activation) activation_18[0][0]'	(None, None, None, 64)	0	['batch_normaliz
mixed1 (Concatenate) [0][0]', [0][0]', [0][0]', [0][0]'	(None, None, None, 288)	0	['activation_12 'activation_14 'activation_17 'activation_18
conv2d_22 (Conv2D)	(None, None, None, 64)	18432	['mixed1[0][0]']
batch_normalization_22 (BatchN [0]'] ormalization)	(None, None, None, 64)	192	['conv2d_22[0]
activation_22 (Activation) activation_22[0][0]'	(None, None, None, 64)	0	['batch_normaliz
conv2d_20 (Conv2D)	(None, None, None, 48)	13824	['mixed1[0][0]']
conv2d_23 (Conv2D) [0][0]'	(None, None, None, 96)	55296	['activation_22
batch_normalization_20 (BatchN [0]'] ormalization)	(None, None, None, 48)	144	['conv2d_20[0]
batch_normalization_23 (BatchN [0]'] ormalization)	(None, None, None, 96)	288	['conv2d_23[0]
activation_20 (Activation) activation_20[0][0]'	(None, None, None, 48)	0	['batch_normaliz
activation_23 (Activation) activation_23[0][0]'	(None, None, None, 96)	0	['batch_normaliz

average_pooling2d_2 (AveragePooling2D)	(None, None, None, 288)	0	['mixed1[0][0]']
conv2d_19 (Conv2D)	(None, None, None, 64)	18432	['mixed1[0][0]']
conv2d_21 (Conv2D) [0][0]']	(None, None, None, 64)	76800	['activation_20
conv2d_24 (Conv2D) [0][0]']	(None, None, None, 96)	82944	['activation_23
conv2d_25 (Conv2D) g2d_2[0][0]']	(None, None, None, 64)	18432	['average_poolin
batch_normalization_19 (BatchNormalization)	(None, None, None, 64)	192	['conv2d_19[0]
batch_normalization_21 (BatchNormalization)	(None, None, None, 64)	192	['conv2d_21[0]
batch_normalization_24 (BatchNormalization)	(None, None, None, 96)	288	['conv2d_24[0]
batch_normalization_25 (BatchNormalization)	(None, None, None, 64)	192	['conv2d_25[0]
activation_19 (Activation) ation_19[0][0]']	(None, None, None, 64)	0	['batch_normaliz
activation_21 (Activation) ation_21[0][0]']	(None, None, None, 64)	0	['batch_normaliz
activation_24 (Activation) ation_24[0][0]']	(None, None, None, 96)	0	['batch_normaliz
activation_25 (Activation) ation_25[0][0]']	(None, None, None, 64)	0	['batch_normaliz
mixed2 (Concatenate) [0][0]', [0][0]', [0][0]', [0][0]']	(None, None, None, 288)	0	['activation_19 'activation_21 'activation_24 'activation_25
conv2d_27 (Conv2D)	(None, None, None, 18432)	18432	['mixed2[0][0]']

	64)		
batch_normalization_27 (Batch Normalization)	(None, None, None, 64)	192	['conv2d_27[0][0]']
activation_27 (Activation)	(None, None, None, 64)	0	['batch_normalization_27[0][0]']
conv2d_28 (Conv2D)	(None, None, None, 96)	55296	['activation_27[0][0]']
batch_normalization_28 (Batch Normalization)	(None, None, None, 96)	288	['conv2d_28[0][0]']
activation_28 (Activation)	(None, None, None, 96)	0	['batch_normalization_28[0][0]']
conv2d_26 (Conv2D)	(None, None, None, 384)	995328	['mixed2[0][0]']
conv2d_29 (Conv2D)	(None, None, None, 96)	82944	['activation_28[0][0]']
batch_normalization_26 (Batch Normalization)	(None, None, None, 384)	1152	['conv2d_26[0][0]']
batch_normalization_29 (Batch Normalization)	(None, None, None, 96)	288	['conv2d_29[0][0]']
activation_26 (Activation)	(None, None, None, 384)	0	['batch_normalization_26[0][0]']
activation_29 (Activation)	(None, None, None, 96)	0	['batch_normalization_29[0][0]']
max_pooling2d_2 (MaxPooling2D)	(None, None, None, 288)	0	['mixed2[0][0]']
mixed3 (Concatenate)	(None, None, None, 768)	0	['activation_26[0][0]', 'activation_29[0][0]', 'max_pooling2d_2[0][0]']
conv2d_34 (Conv2D)	(None, None, None, 128)	98304	['mixed3[0][0]']
batch_normalization_34 (Batch Normalization)	(None, None, None, 384)	384	['conv2d_34[0][0]']

ormalization)	128)		
activation_34 (Activation) ation_34[0][0]'	(None, None, None, 0 128)		['batch_normaliz
conv2d_35 (Conv2D) [0][0]'	(None, None, None, 114688 128)		['activation_34
batch_normalization_35 (BatchN [0]') ormalization)	(None, None, None, 384 128)		['conv2d_35[0]
activation_35 (Activation) ation_35[0][0]'	(None, None, None, 0 128)		['batch_normaliz
conv2d_31 (Conv2D)	(None, None, None, 98304 128)		['mixed3[0][0]']
conv2d_36 (Conv2D) [0][0]'	(None, None, None, 114688 128)		['activation_35
batch_normalization_31 (BatchN [0]') ormalization)	(None, None, None, 384 128)		['conv2d_31[0]
batch_normalization_36 (BatchN [0]') ormalization)	(None, None, None, 384 128)		['conv2d_36[0]
activation_31 (Activation) ation_31[0][0]'	(None, None, None, 0 128)		['batch_normaliz
activation_36 (Activation) ation_36[0][0]'	(None, None, None, 0 128)		['batch_normaliz
conv2d_32 (Conv2D) [0][0]'	(None, None, None, 114688 128)		['activation_31
conv2d_37 (Conv2D) [0][0]'	(None, None, None, 114688 128)		['activation_36
batch_normalization_32 (BatchN [0]') ormalization)	(None, None, None, 384 128)		['conv2d_32[0]
batch_normalization_37 (BatchN [0]') ormalization)	(None, None, None, 384 128)		['conv2d_37[0]
activation_32 (Activation) ation_32[0][0]'	(None, None, None, 0 128)		['batch_normaliz

activation_37 (Activation) activation_37[0][0]'	(None, None, None, 0 128)	0	['batch_normaliz
average_pooling2d_3 (AveragePo oling2D)	(None, None, None, 768)	0	['mixed3[0][0]']
conv2d_30 (Conv2D)	(None, None, None, 192)	147456	['mixed3[0][0]']
conv2d_33 (Conv2D) [0][0]'	(None, None, None, 192)	172032	['activation_32
conv2d_38 (Conv2D) [0][0]'	(None, None, None, 192)	172032	['activation_37
conv2d_39 (Conv2D) g2d_3[0][0]'	(None, None, None, 192)	147456	['average_poolin
batch_normalization_30 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_30[0]
batch_normalization_33 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_33[0]
batch_normalization_38 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_38[0]
batch_normalization_39 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_39[0]
activation_30 (Activation) ation_30[0][0]'	(None, None, None, 192)	0	['batch_normaliz
activation_33 (Activation) ation_33[0][0]'	(None, None, None, 192)	0	['batch_normaliz
activation_38 (Activation) ation_38[0][0]'	(None, None, None, 192)	0	['batch_normaliz
activation_39 (Activation) ation_39[0][0]'	(None, None, None, 192)	0	['batch_normaliz
mixed4 (Concatenate) [0][0]', [0][0]',	(None, None, None, 768)	0	['activation_30 'activation_33 'activation_38

[0][0]',				'activation_39
[0][0]']				
conv2d_44 (Conv2D)	(None, None, None, 160)	122880		['mixed4[0][0]']
batch_normalization_44 (Batch Normalization)	(None, None, None, 160)	480		['conv2d_44[0]
activation_44 (Activation)	(None, None, None, 160)	0		['batch_normaliz
conv2d_45 (Conv2D)	(None, None, None, 160)	179200		['activation_44
batch_normalization_45 (Batch Normalization)	(None, None, None, 160)	480		['conv2d_45[0]
activation_45 (Activation)	(None, None, None, 160)	0		['batch_normaliz
conv2d_41 (Conv2D)	(None, None, None, 160)	122880		['mixed4[0][0]']
conv2d_46 (Conv2D)	(None, None, None, 160)	179200		['activation_45
batch_normalization_41 (Batch Normalization)	(None, None, None, 160)	480		['conv2d_41[0]
batch_normalization_46 (Batch Normalization)	(None, None, None, 160)	480		['conv2d_46[0]
activation_41 (Activation)	(None, None, None, 160)	0		['batch_normaliz
activation_46 (Activation)	(None, None, None, 160)	0		['batch_normaliz
conv2d_42 (Conv2D)	(None, None, None, 160)	179200		['activation_41
conv2d_47 (Conv2D)	(None, None, None, 160)	179200		['activation_46
batch_normalization_42 (Batch Normalization)	(None, None, None, 160)	480		['conv2d_42[0]

ormalization)	160)		
batch_normalization_47 (BatchN [0]')	(None, None, None, 480		['conv2d_47[0]
ormalization)	160)		
activation_42 (Activation) ation_42[0][0]')	(None, None, None, 0		['batch_normaliz
	160)		
activation_47 (Activation) ation_47[0][0]')	(None, None, None, 0		['batch_normaliz
	160)		
average_pooling2d_4 (AveragePo oling2D)	(None, None, None, 0		['mixed4[0][0]')
	768)		
conv2d_40 (Conv2D)	(None, None, None, 147456		['mixed4[0][0]')
	192)		
conv2d_43 (Conv2D) [0][0]')	(None, None, None, 215040		['activation_42
	192)		
conv2d_48 (Conv2D) [0][0]')	(None, None, None, 215040		['activation_47
	192)		
conv2d_49 (Conv2D) g2d_4[0][0]')	(None, None, None, 147456		['average_poolin
	192)		
batch_normalization_40 (BatchN [0]')	(None, None, None, 576		['conv2d_40[0]
ormalization)	192)		
batch_normalization_43 (BatchN [0]')	(None, None, None, 576		['conv2d_43[0]
ormalization)	192)		
batch_normalization_48 (BatchN [0]')	(None, None, None, 576		['conv2d_48[0]
ormalization)	192)		
batch_normalization_49 (BatchN [0]')	(None, None, None, 576		['conv2d_49[0]
ormalization)	192)		
activation_40 (Activation) ation_40[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
activation_43 (Activation) ation_43[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
activation_48 (Activation) ation_48[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		

activation_49 (Activation) activation_49[0][0]'	(None, None, None, 0 192)	['batch_normaliz
mixed5 (Concatenate) [0][0]', [0][0]', [0][0]', [0][0]'	(None, None, None, 0 768)	['activation_40 'activation_43 'activation_48 'activation_49
conv2d_54 (Conv2D)	(None, None, None, 122880 160)	['mixed5[0][0]'
batch_normalization_54 (BatchN [0]') ormalization)	(None, None, None, 480 160)	['conv2d_54[0]
activation_54 (Activation) ation_54[0][0]'	(None, None, None, 0 160)	['batch_normaliz
conv2d_55 (Conv2D) [0][0]'	(None, None, None, 179200 160)	['activation_54
batch_normalization_55 (BatchN [0]') ormalization)	(None, None, None, 480 160)	['conv2d_55[0]
activation_55 (Activation) ation_55[0][0]'	(None, None, None, 0 160)	['batch_normaliz
conv2d_51 (Conv2D)	(None, None, None, 122880 160)	['mixed5[0][0]'
conv2d_56 (Conv2D) [0][0]'	(None, None, None, 179200 160)	['activation_55
batch_normalization_51 (BatchN [0]') ormalization)	(None, None, None, 480 160)	['conv2d_51[0]
batch_normalization_56 (BatchN [0]') ormalization)	(None, None, None, 480 160)	['conv2d_56[0]
activation_51 (Activation) ation_51[0][0]'	(None, None, None, 0 160)	['batch_normaliz
activation_56 (Activation) ation_56[0][0]'	(None, None, None, 0 160)	['batch_normaliz
conv2d_52 (Conv2D)	(None, None, None, 179200)	['activation_51

[0][0]']	160)		
conv2d_57 (Conv2D) [0][0]']	(None, None, None, 160)	179200	['activation_56
batch_normalization_52 (Batch Normalization) [0]']	(None, None, None, 160)	480	['conv2d_52[0]
batch_normalization_57 (Batch Normalization) [0]']	(None, None, None, 160)	480	['conv2d_57[0]
activation_52 (Activation) ation_52[0][0]']	(None, None, None, 160)	0	['batch_normaliz
activation_57 (Activation) ation_57[0][0]']	(None, None, None, 160)	0	['batch_normaliz
average_pooling2d_5 (Average Pooling2D)	(None, None, None, 768)	0	['mixed5[0][0]']
conv2d_50 (Conv2D)	(None, None, None, 192)	147456	['mixed5[0][0]']
conv2d_53 (Conv2D) [0][0]']	(None, None, None, 192)	215040	['activation_52
conv2d_58 (Conv2D) [0][0]']	(None, None, None, 192)	215040	['activation_57
conv2d_59 (Conv2D) g2d_5[0][0]']	(None, None, None, 192)	147456	['average_poolin
batch_normalization_50 (Batch Normalization) [0]']	(None, None, None, 192)	576	['conv2d_50[0]
batch_normalization_53 (Batch Normalization) [0]']	(None, None, None, 192)	576	['conv2d_53[0]
batch_normalization_58 (Batch Normalization) [0]']	(None, None, None, 192)	576	['conv2d_58[0]
batch_normalization_59 (Batch Normalization) [0]']	(None, None, None, 192)	576	['conv2d_59[0]
activation_50 (Activation) ation_50[0][0]']	(None, None, None, 192)	0	['batch_normaliz

activation_53 (Activation) activation_53[0][0]'	(None, None, None, 0 192)	['batch_normaliz
activation_58 (Activation) activation_58[0][0]'	(None, None, None, 0 192)	['batch_normaliz
activation_59 (Activation) activation_59[0][0]'	(None, None, None, 0 192)	['batch_normaliz
mixed6 (Concatenate) [0][0]', [0][0]', [0][0]', [0][0]'	(None, None, None, 0 768)	['activation_50 'activation_53 'activation_58 'activation_59
conv2d_64 (Conv2D)	(None, None, None, 147456 192)	['mixed6[0][0]']
batch_normalization_64 (BatchN [0]') ormalization)	(None, None, None, 576 192)	['conv2d_64[0]
activation_64 (Activation) activation_64[0][0]'	(None, None, None, 0 192)	['batch_normaliz
conv2d_65 (Conv2D) [0][0]'	(None, None, None, 258048 192)	['activation_64
batch_normalization_65 (BatchN [0]') ormalization)	(None, None, None, 576 192)	['conv2d_65[0]
activation_65 (Activation) activation_65[0][0]'	(None, None, None, 0 192)	['batch_normaliz
conv2d_61 (Conv2D)	(None, None, None, 147456 192)	['mixed6[0][0]']
conv2d_66 (Conv2D) [0][0]'	(None, None, None, 258048 192)	['activation_65
batch_normalization_61 (BatchN [0]') ormalization)	(None, None, None, 576 192)	['conv2d_61[0]
batch_normalization_66 (BatchN [0]') ormalization)	(None, None, None, 576 192)	['conv2d_66[0]

activation_61 (Activation) activation_61[0][0]'	(None, None, None, 192)	0	['batch_normaliz
activation_66 (Activation) activation_66[0][0]'	(None, None, None, 192)	0	['batch_normaliz
conv2d_62 (Conv2D) [0][0]'	(None, None, None, 192)	258048	['activation_61
conv2d_67 (Conv2D) [0][0]'	(None, None, None, 192)	258048	['activation_66
batch_normalization_62 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_62[0]
batch_normalization_67 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_67[0]
activation_62 (Activation) activation_62[0][0]'	(None, None, None, 192)	0	['batch_normaliz
activation_67 (Activation) activation_67[0][0]'	(None, None, None, 192)	0	['batch_normaliz
average_pooling2d_6 (AveragePo oling2D)	(None, None, None, 768)	0	['mixed6[0][0]'
conv2d_60 (Conv2D)	(None, None, None, 192)	147456	['mixed6[0][0]'
conv2d_63 (Conv2D) [0][0]'	(None, None, None, 192)	258048	['activation_62
conv2d_68 (Conv2D) [0][0]'	(None, None, None, 192)	258048	['activation_67
conv2d_69 (Conv2D) g2d_6[0][0]'	(None, None, None, 192)	147456	['average_poolin
batch_normalization_60 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_60[0]
batch_normalization_63 (BatchN [0]') ormalization)	(None, None, None, 192)	576	['conv2d_63[0]
batch_normalization_68 (BatchN [0]')	(None, None, None, 192)	576	['conv2d_68[0]

ormalization)	192)		
batch_normalization_69 (BatchN [0]')	(None, None, None, 576		['conv2d_69[0]
ormalization)	192)		
activation_60 (Activation) ation_60[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
activation_63 (Activation) ation_63[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
activation_68 (Activation) ation_68[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
activation_69 (Activation) ation_69[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
mixed7 (Concatenate) [0][0]'	(None, None, None, 0		['activation_60
	768)		'activation_63
[0][0]'			'activation_68
[0][0]'			'activation_69
[0][0]')			
conv2d_72 (Conv2D)	(None, None, None, 147456		['mixed7[0][0]')
	192)		
batch_normalization_72 (BatchN [0]')	(None, None, None, 576		['conv2d_72[0]
ormalization)	192)		
activation_72 (Activation) ation_72[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
conv2d_73 (Conv2D) [0][0]')	(None, None, None, 258048		['activation_72
	192)		
batch_normalization_73 (BatchN [0]')	(None, None, None, 576		['conv2d_73[0]
ormalization)	192)		
activation_73 (Activation) ation_73[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
conv2d_70 (Conv2D)	(None, None, None, 147456		['mixed7[0][0]')
	192)		
conv2d_74 (Conv2D) [0][0]')	(None, None, None, 258048		['activation_73
	192)		

batch_normalization_70 (Batch Normalization)	(None, None, None, 192)	576	['conv2d_70[0][0]']
batch_normalization_74 (Batch Normalization)	(None, None, None, 192)	576	['conv2d_74[0][0]']
activation_70 (Activation)	(None, None, None, 192)	0	['batch_normalization_70[0][0][0]']
activation_74 (Activation)	(None, None, None, 192)	0	['batch_normalization_74[0][0][0]']
conv2d_71 (Conv2D)	(None, None, None, 320)	552960	['activation_70[0][0][0]']
conv2d_75 (Conv2D)	(None, None, None, 192)	331776	['activation_74[0][0][0]']
batch_normalization_71 (Batch Normalization)	(None, None, None, 320)	960	['conv2d_71[0][0][0]']
batch_normalization_75 (Batch Normalization)	(None, None, None, 192)	576	['conv2d_75[0][0][0]']
activation_71 (Activation)	(None, None, None, 320)	0	['batch_normalization_71[0][0][0][0]']
activation_75 (Activation)	(None, None, None, 192)	0	['batch_normalization_75[0][0][0][0]']
max_pooling2d_3 (MaxPooling2D)	(None, None, None, 768)	0	['mixed7[0][0][0][0]']
mixed8 (Concatenate)	(None, None, None, 1280)	0	['activation_71[0][0][0][0]', 'activation_75[0][0][0][0]', 'max_pooling2d_3[0][0][0][0]']
conv2d_80 (Conv2D)	(None, None, None, 448)	573440	['mixed8[0][0][0][0]']
batch_normalization_80 (Batch Normalization)	(None, None, None, 448)	1344	['conv2d_80[0][0][0][0]']
activation_80 (Activation)	(None, None, None, 448)	0	['batch_normalization_80[0][0][0][0][0]']

	448)			
conv2d_77 (Conv2D)	(None, None, None, 384)	491520		['mixed8[0][0]']
conv2d_81 (Conv2D) [0][0]']	(None, None, None, 384)	1548288		['activation_80
batch_normalization_77 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_77[0]
batch_normalization_81 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_81[0]
activation_77 (Activation) ation_77[0][0]']	(None, None, None, 384)	0		['batch_normaliz
activation_81 (Activation) ation_81[0][0]']	(None, None, None, 384)	0		['batch_normaliz
conv2d_78 (Conv2D) [0][0]']	(None, None, None, 384)	442368		['activation_77
conv2d_79 (Conv2D) [0][0]']	(None, None, None, 384)	442368		['activation_77
conv2d_82 (Conv2D) [0][0]']	(None, None, None, 384)	442368		['activation_81
conv2d_83 (Conv2D) [0][0]']	(None, None, None, 384)	442368		['activation_81
average_pooling2d_7 (Average Pooling2D)	(None, None, None, 1280)	0		['mixed8[0][0]']
conv2d_76 (Conv2D)	(None, None, None, 320)	409600		['mixed8[0][0]']
batch_normalization_78 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_78[0]
batch_normalization_79 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_79[0]
batch_normalization_82 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_82[0]
batch_normalization_83 (Batch Normalization)	(None, None, None, 384)	1152		['conv2d_83[0]

[0]']				
ormalization)	384)			
conv2d_84 (Conv2D)	(None, None, None,	245760		['average_poolin
g2d_7[0][0]']	192)			
batch_normalization_76 (BatchN	(None, None, None,	960		['conv2d_76[0]
[0]']				
ormalization)	320)			
activation_78 (Activation)	(None, None, None,	0		['batch_normaliz
ation_78[0][0]']	384)			
activation_79 (Activation)	(None, None, None,	0		['batch_normaliz
ation_79[0][0]']	384)			
activation_82 (Activation)	(None, None, None,	0		['batch_normaliz
ation_82[0][0]']	384)			
activation_83 (Activation)	(None, None, None,	0		['batch_normaliz
ation_83[0][0]']	384)			
batch_normalization_84 (BatchN	(None, None, None,	576		['conv2d_84[0]
[0]']				
ormalization)	192)			
activation_76 (Activation)	(None, None, None,	0		['batch_normaliz
ation_76[0][0]']	320)			
mixed9_0 (Concatenate)	(None, None, None,	0		['activation_78
[0][0]',	768)			'activation_79
[0][0]']				
concatenate (Concatenate)	(None, None, None,	0		['activation_82
[0][0]',	768)			'activation_83
[0][0]']				
activation_84 (Activation)	(None, None, None,	0		['batch_normaliz
ation_84[0][0]']	192)			
mixed9 (Concatenate)	(None, None, None,	0		['activation_76
[0][0]',	2048)			'mixed9_0[0]
[0]',				'concatenate[0]
[0]',				'activation_84
[0][0]']				
conv2d_89 (Conv2D)	(None, None, None,	917504		['mixed9[0][0]']
	448)			

batch_normalization_89 (Batch Normalization)	(None, None, None, 448)	1344	['conv2d_89[0][0]']
activation_89 (Activation)	(None, None, None, 448)	0	['batch_normalization_89[0][0]']
conv2d_86 (Conv2D)	(None, None, None, 384)	786432	['mixed9[0][0]']
conv2d_90 (Conv2D)	(None, None, None, 384)	1548288	['activation_89[0][0]']
batch_normalization_86 (Batch Normalization)	(None, None, None, 384)	1152	['conv2d_86[0][0]']
batch_normalization_90 (Batch Normalization)	(None, None, None, 384)	1152	['conv2d_90[0][0]']
activation_86 (Activation)	(None, None, None, 384)	0	['batch_normalization_86[0][0]']
activation_90 (Activation)	(None, None, None, 384)	0	['batch_normalization_90[0][0]']
conv2d_87 (Conv2D)	(None, None, None, 384)	442368	['activation_86[0][0]']
conv2d_88 (Conv2D)	(None, None, None, 384)	442368	['activation_86[0][0]']
conv2d_91 (Conv2D)	(None, None, None, 384)	442368	['activation_90[0][0]']
conv2d_92 (Conv2D)	(None, None, None, 384)	442368	['activation_90[0][0]']
average_pooling2d_8 (AveragePooling2D)	(None, None, None, 2048)	0	['mixed9[0][0]']
conv2d_85 (Conv2D)	(None, None, None, 320)	655360	['mixed9[0][0]']
batch_normalization_87 (Batch Normalization)	(None, None, None, 384)	1152	['conv2d_87[0][0]']
batch_normalization_88 (Batch Normalization)	(None, None, None, 384)	1152	['conv2d_88[0][0]']

ormalization)	384)		
batch_normalization_91 (BatchN [0]')	(None, None, None, 1152		['conv2d_91[0]
ormalization)	384)		
batch_normalization_92 (BatchN [0]')	(None, None, None, 1152		['conv2d_92[0]
ormalization)	384)		
conv2d_93 (Conv2D) g2d_8[0][0]')	(None, None, None, 393216		['average_poolin
	192)		
batch_normalization_85 (BatchN [0]')	(None, None, None, 960		['conv2d_85[0]
ormalization)	320)		
activation_87 (Activation) ation_87[0][0]')	(None, None, None, 0		['batch_normaliz
	384)		
activation_88 (Activation) ation_88[0][0]')	(None, None, None, 0		['batch_normaliz
	384)		
activation_91 (Activation) ation_91[0][0]')	(None, None, None, 0		['batch_normaliz
	384)		
activation_92 (Activation) ation_92[0][0]')	(None, None, None, 0		['batch_normaliz
	384)		
batch_normalization_93 (BatchN [0]')	(None, None, None, 576		['conv2d_93[0]
ormalization)	192)		
activation_85 (Activation) ation_85[0][0]')	(None, None, None, 0		['batch_normaliz
	320)		
mixed9_1 (Concatenate) [0][0]',	(None, None, None, 0		['activation_87
	768)		'activation_88
[0][0]')			
concatenate_1 (Concatenate) [0][0]',	(None, None, None, 0		['activation_91
	768)		'activation_92
[0][0]')			
activation_93 (Activation) ation_93[0][0]')	(None, None, None, 0		['batch_normaliz
	192)		
mixed10 (Concatenate) [0][0]',	(None, None, None, 0		['activation_85
	2048)		'mixed9_1[0]
[0]'			

```

[0][0]',
[0][0]'
'concatenate_1
'activation_93

```

```

=====
=====
Total params: 21,802,784
Trainable params: 21,768,352
Non-trainable params: 34,432

<BatchDataset element_spec=(TensorSpec(shape=(None, 299, 299, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.string, name=None))>
100%|██████████| 125/125 [00:19<00:00, 6.41it/s]

```

Préparation du tokenizer

Le tokenizer va nous servir de dictionnaire. La bibliothèque Keras nous donne les mots les plus communs, nous avons choisi les 5000 premiers (voir la variable `top_k`). On crée ensuite le dictionnaire avec la méthode `fit_on_texts`, il sera basé sur les annotations du dataset Coco train 2014 et attribuera un token (un id entre 1 et 5000) à chaque mot. Ainsi, notre RNN nous renverra un vecteur de tokens que nous traduirons en mots à la fin.

```

In [ ]: # Trouver la taille maximale
def calc_max_length(tensor):
    return max(len(t) for t in tensor)

# Choisir les 5000 mots les plus frequents du vocabulaire
top_k = 5000
#La classe Tokenizer permet de faire du pre-traitement de texte pour reseau de n
tokenizer = tf.keras.preprocessing.text.Tokenizer(num_words=top_k,
                                                    oov_token="<unk>",
                                                    filters='!"#$%&()*+.,-/:;=?@[\`
# Construit un vocabulaire en se basant sur la liste train_captions
tokenizer.fit_on_texts(train_captions)

# Créer Le token qui sert à remplir les annotations pour egaliser leurs longueur
tokenizer.word_index['<pad>'] = 0
tokenizer.index_word[0] = '<pad>'

# Creation des vecteurs(liste de token entiers) à partir des annotations (liste
train_seqs = tokenizer.texts_to_sequences(train_captions)

# Remplir chaque vecteur à jusqu'à la longueur maximale des annotations
cap_vector = tf.keras.preprocessing.sequence.pad_sequences(train_seqs, padding

# Calcule la longueur maximale qui est utilisée pour stocker les poids d'attenti
# Elle servira plus tard pour l'affichage lors de l'évaluation
max_length = calc_max_length(train_seqs)

```

Split test/train

Nous créons les jeux d'entraînement et de test, pour les photos ainsi que les annotations.
Nous affichons leur longueur pour s'assurer de la bonne exécution de la fonction.

```
In [ ]: img_name_train, img_name_val, cap_train, cap_val = train_test_split(img_name_vec
                                                    cap_vector,
                                                    test_size=0.
                                                    random_state

len(img_name_train), len(cap_train), len(img_name_val), len(cap_val)

Out[ ]: (8004, 8004, 2001, 2001)
```

Entraînement

Définition des paramètres

```
In [ ]: # N'hésitez pas à modifier ces paramètres en fonction de votre machine
BATCH_SIZE = 32 # taille du batch
BUFFER_SIZE = 8000 # taille du buffer pour mélanger les données
embedding_dim = 256
units = 512 # Taille de la couche cachée dans le RNN
vocab_size = top_k + 1
num_steps = len(img_name_train) // BATCH_SIZE

# La forme du vecteur extrait à partir d'InceptionV3 est (64, 2048)
# Les deux variables suivantes représentent la forme de ce vecteur
features_shape = 2048
attention_features_shape = 64

# Fonction qui charge les fichiers numpy des images prétraitées
def map_func(img_name, cap):
    img_tensor = np.load(img_name.decode('utf-8')+'.npy')
    return img_tensor, cap

# Création d'un dataset de "Tensor"s (sert à représenter de grands datasets)
# Le dataset est créé à partir de "img_name_train" et "cap_train"
dataset = tf.data.Dataset.from_tensor_slices((img_name_train, cap_train))

# L'utilisation de map permet de charger les fichiers numpy (possiblement en parallèle)
dataset = dataset.map(lambda item1, item2: tf.numpy_function(
    map_func, [item1, item2], [tf.float32, tf.int32]),
    num_parallel_calls=tf.data.experimental.AUTOTUNE)

# Mélanger les données et les diviser en batches
dataset = dataset.shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
dataset = dataset.prefetch(buffer_size=tf.data.experimental.AUTOTUNE)
```

Encodeur CNN

On passe la sortie d'InceptionV3 dans une couche dense afin de vectoriser nos features.

```
In [ ]: class CNN_Encoder(tf.keras.Model):
    def __init__(self, embedding_dim):
        super(CNN_Encoder, self).__init__()
        # shape after fc == (batch_size, 64, embedding_dim)
        self.fc = tf.keras.layers.Dense(embedding_dim)

    def call(self, x):
        x = self.fc(x)
        x = tf.nn.relu(x)
        return x
```

Décodeur RNN

Avec nos features vectorisées, on va ensuite Les passer dans notre RNN, ou notre mécanisme d'attention, des GRU et des Denses vont gerer le captioning de l'image.

Mécanisme d'attention

Le mécanisme d'attention permet au décodeur de se concentrer sur les parties les plus pertinentes de l'image lors de la génération de chaque mot de la légende.

A chaque étape du décodage, le mécanisme d'attention calcule un score d'attention pour chaque état caché de l'encodeur. Ce score reflète l'importance relative de cet état caché pour le mot en cours de génération. Le calcul de ces scores prend en compte deux notions importantes : le **contexte** et les **sous-régions**.

- L'image est divisée en plusieurs sous-régions, chacune correspondant à une partie spécifique de l'image.
- Le contexte représente l'état caché du décodeur à l'étape précédente, Il reflète la compréhension du langage acquise jusqu'à présent par le décodeur. Les scores d'attention sont ensuite normalisés et utilisés pour pondérer les états cachés de l'encodeur. Le contexte pondéré ainsi obtenu représente une représentation synthétique des informations visuelles les plus pertinentes pour le mot en cours, en tenant compte à la fois du contexte linguistique et des sous-régions de l'image.

En bref, le mécanisme d'attention calcule l'importance de chaque partie de l'image pour chaque mot de la légende.

```
In [ ]: class BahdanauAttention(tf.keras.Model):
    def __init__(self, units):
        super(BahdanauAttention, self).__init__()
        self.W1 = tf.keras.layers.Dense(units)
        self.W2 = tf.keras.layers.Dense(units)
        self.V = tf.keras.layers.Dense(1)

    def call(self, features, hidden):
        # features(CNN_encoder output) forme == (batch_size, 64, embedding_dim)

        # forme de la couche cachée == (batch_size, hidden_size)
        hidden_with_time_axis = tf.expand_dims(hidden, 1)

        # score shape == (batch_size, 64, hidden_size)
```

```

score = tf.nn.tanh(self.W1(features) + self.W2(hidden_with_time_axis))
          #(BATCH_SIZE,64,hidden_size) + (BATCH_SIZE,1,hidden_size)

# attention_weights shape == (batch_size, 64, 1)
# You get 1 at the last axis because you are applying score to self.V
attention_weights = tf.nn.softmax(self.V(score), axis=1)

# context_vector shape after sum == (batch_size, hidden_size)
context_vector = attention_weights * features
context_vector = tf.reduce_sum(context_vector, axis=1)

return context_vector, attention_weights

```

Décodeur

La fonction de call du RNN va générer un mot par rapport a l'hidden state, aux features d'entrées, pour renvoyer une sortie et un nouveau hidden state

```

In [ ]: class RNN_Decoder(tf.keras.Model):
        def __init__(self, embedding_dim, units, vocab_size):
            super(RNN_Decoder, self).__init__()
            self.units = units

            self.embedding = tf.keras.layers.Embedding(vocab_size, embedding_dim)
            self.gru = tf.keras.layers.GRU(self.units,
                                             return_sequences=True,
                                             return_state=True,
                                             recurrent_initializer='glorot_uniform')

            self.fc1 = tf.keras.layers.Dense(self.units)
            self.fc2 = tf.keras.layers.Dense(vocab_size)

            self.attention = BahdanauAttention(self.units)

        def call(self, x, features, hidden):
            # L'attention est défini par un modèle a part
            context_vector, attention_weights = self.attention(features, hidden)
            # Passage du mot courant à la couche embedding
            x = self.embedding(x)

            # Concaténation
            x = tf.concat([tf.expand_dims(context_vector, 1), x], axis=-1)

            # Passage du vecteur concaténé à la gru
            output, state = self.gru(x)

            y = tf.reshape(output, (-1, x.shape[2]))

            # Couche dense
            y = x = self.fc1(y)

```

```

        # Couche dense
        y = self.fc2(x)

    return y, state, attention_weights

def reset_state(self, batch_size):
    return tf.zeros((batch_size, self.units))

```

Combinaison encodeur + décodeur

```

In [ ]: # Création de l'encodeur
encoder = CNN_Encoder(embedding_dim)

# Création du décodeur
decoder = RNN_Decoder(embedding_dim, units, vocab_size)

```

Prepare training loop

Optimizer and Loss

On prendra Adam pour optimiser notre learning rate, puis la Sparse Categorical Cross Entropy

```

In [ ]: # Optimiseur ADAM
optimizer = tf.keras.optimizers.Adam(0.001)

# La fonction de perte
loss_object = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True, reduction='none')

def loss_function(real, pred):
    mask = tf.math.logical_not(tf.math.equal(real, 0))
    loss_ = loss_object(real, pred)

    mask = tf.cast(mask, dtype=loss_.dtype)
    loss_ *= mask

    return tf.reduce_mean(loss_)

```

Callbacks

On fera 2 callbacks :

- Early stopping : Si notre loss de validation augmente sur plusieurs epoch (nombre défini), on va arreter l'entrainement car on overfit. on économise ainsi du temps.
- Loss record: On va enregistrer nos loss de validation pour comparer nos modèles entre eux via tensorboard.

```

In [ ]: #CALLBACKS

```

```

def get_val_loss(dataset, encoder, decoder):
    total_loss = 0
    for (batch, (img_tensor, target)) in enumerate(dataset):
        loss = 0
        # Initialisation de l'état caché pour chaque batch
        hidden = decoder.reset_state(batch_size=target.shape[0])
        #print(tokenizer.word_index)

        # Initialiser l'entrée du décodeur
        dec_input = tf.expand_dims([tokenizer.word_index['<start>']] * target.sh

        features = encoder(img_tensor)

        for i in range(1, target.shape[1]):
            # Prédiction des i-èmes mot du batch avec le décodeur
            predictions, hidden, _ = decoder(dec_input, features, hidden)
            loss += loss_function(target[:, i], predictions)

            # Le mot correct à l'étape i est donné en entrée à l'étape (i+1)
            dec_input = tf.expand_dims(target[:, i], 1)

        t_loss = (loss / int(target.shape[1]))

        total_loss += t_loss

    return total_loss

class Callbacker():
    def __init__(self, tensorboard = True, early_stopping = True, es_patience =

        time = datetime.datetime.now()
        self.training_name = f"{time.day}_{time.month}_{time.year}_{time.hour}h{
        #self.best_loss = np.Inf
        self.best_val_loss = np.Inf
        self.wait = 0
        self.stopped_epoch = 0

        self.btensorboard = tensorboard
        self.bearly_stopping = early_stopping
        self.es_patience = es_patience
        self.save_model = save_model

        self.stop_training = False

        if self.btensorboard == True:
            self.writer= tf.summary.create_file_writer(f"tensorboard/{self.train

    def epoch_callback(self, encoder_model, decoder_model, num_epoch:int, curren
        """
        at each epoch, this function will be launched, we will record our weight
        this function need as parameters:
        - encoder model: the encoder model (usually RNN).
        - decoder: the decoder model (usually RNN)
        - num epoch : the current epoch number

```

```

- current_loss : the current train loss
- current_val_loss : the current loss for validation
"""
print(f"The average loss for epoch {num_epoch} is loss :{current_loss},

if self.btensorboard == True:
    with self.writer.as_default():
        tf.summary.scalar('loss', current_loss, step=num_epoch)
        tf.summary.scalar('val_loss', current_val_loss, step=num_epoch)

if np.less(current_val_loss, self.best_val_loss):
    #self.best_loss = current_loss
    self.best_val_loss = current_val_loss
    self.wait = 0
    self.encoder_best_weights = encoder_model.get_weights()
    self.decoder_best_weights = decoder_model.get_weights()
    # Record the best weights if current results is better (less).
    if self.save_model == True:
        encoder_model.save(f'./models/{self.training_name}/encoder.tf')
        decoder_model.save(f'./models/{self.training_name}/decoder.tf')
else:
    if self.bearly_stopping == True:
        self.wait += 1
        if self.wait >= self.es_patience:
            self.stop_training = True
            print("Restoring model weights from the end of the best epoch")
            encoder_model.set_weights(self.encoder_best_weights)
            decoder_model.set_weights(self.decoder_best_weights)

```

Training step function

On définit ici notre fonction `train_step`, qui va prédire sur un batch, calculer la loss et appliquer la gradient backpropagation.

```

In [ ]: loss_plot = []
@tf.function
def train_step(img_tensor, target):
    loss = 0

    # Initialisation de l'état caché pour chaque batch
    hidden = decoder.reset_state(batch_size=target.shape[0])

    #print(tokenizer.word_index)

    # Initialiser l'entrée du décodeur
    dec_input = tf.expand_dims([tokenizer.word_index['<start>']] * target.shape[0], axis=-1)

    with tf.GradientTape() as tape: # Offre la possibilité de calculer le gradient

        features = encoder(img_tensor)

        for i in range(1, target.shape[1]):
            # Prédiction des i-èmes mot du batch avec le décodeur
            predictions, hidden, _ = decoder(dec_input, features, hidden)

```



```

        loss += loss_function(target[:, i], predictions)

        # Le mot correct à l'étape i est donné en entrée à l'étape (i+1)
        dec_input = tf.expand_dims(target[:, i], 1)

    total_loss = (loss / int(target.shape[1]))

    trainable_variables = encoder.trainable_variables + decoder.trainable_variables

    gradients = tape.gradient(loss, trainable_variables)

    optimizer.apply_gradients(zip(gradients, trainable_variables))

    return loss, total_loss

```

Training

Voici la boucle complète d'entraînement, ou on lance notre train_step, et où on réalise les callbacks.

```

In [ ]: EPOCHS = 30

# Creation d'un dataset de "Tensor"s (sert à représenter de grands dataset)
# Le dataset est créé à partir de "img_name_train" et "cap_train"
val_dataset = tf.data.Dataset.from_tensor_slices((img_name_val, cap_val))

# L'utilisation de map permet de charger les fichiers numpy (possiblement en parallèle)
val_dataset = dataset.map(lambda item1, item2: tf.numpy_function(
    map_func, [item1, item2], [tf.float32, tf.int32]),
    num_parallel_calls=tf.data.experimental.AUTOTUNE)

# Mélanger les données et les diviser en batches
val_dataset = dataset.shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
val_dataset = dataset.prefetch(buffer_size=tf.data.experimental.AUTOTUNE)

callback = Callbacker(es_patience= 3)

# create the directory
os.makedirs(f'./models/{callback.training_name}')
# save of the tokenizer
with open(f'./models/{callback.training_name}/tokenizer.pickle', 'wb') as handle:
    pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)

for epoch in range(EPOCHS):
    start = time.time()
    total_loss = 0

    for (batch, (img_tensor, target)) in enumerate(dataset):
        batch_loss, t_loss = train_step(img_tensor, target)
        total_loss += t_loss

        if batch % 100 == 0:
            print ('Epoch {} Batch {} Loss {:.4f}'.format(
                epoch + 1, batch, batch_loss.numpy() / int(target.shape[1])))

```

```

#VALIDATION-----
val_loss = get_val_loss(val_dataset,encoder,decoder)
#-----

#CALLBACK -----
callbackker.epoch_callback(encoder, decoder, epoch, total_loss/num_steps, val
#-----
# sauvegarde de la perte
loss_plot.append(total_loss / num_steps)

print ('Epoch {} Loss {:.6f}'.format(epoch + 1,
                                     total_loss/num_steps))
print ('Time taken for 1 epoch {} sec\n'.format(time.time() - start))

# Affichage de la courbe d'entrainement
plt.plot(loss_plot)
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss Plot')
plt.show()

```

Epoch 1 Batch 0 Loss 2.9019

Epoch 1 Batch 100 Loss 1.7013

Epoch 1 Batch 200 Loss 1.4208

The average loss for epoch 0 is loss :1.62021005153656, val loss : 1.3490633964538574

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Epoch 1 Loss 1.620210

Time taken for 1 epoch 174.15002179145813 sec

Epoch 2 Batch 0 Loss 1.2433

Epoch 2 Batch 100 Loss 1.2151

Epoch 2 Batch 200 Loss 1.2811

The average loss for epoch 1 is loss :1.300060510635376, val loss : 1.1758900880813599

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Epoch 2 Loss 1.300061

Time taken for 1 epoch 135.76465582847595 sec

Epoch 3 Batch 0 Loss 1.1567

Epoch 3 Batch 100 Loss 1.1922

Epoch 3 Batch 200 Loss 1.0614

The average loss for epoch 2 is loss :1.164872646331787, val loss : 1.0534507036209106

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```
Epoch 3 Loss 1.164873
```

```
Time taken for 1 epoch 129.08605432510376 sec
```

```
Epoch 4 Batch 0 Loss 0.9683
```

```
Epoch 4 Batch 100 Loss 1.1420
```

```
Epoch 4 Batch 200 Loss 1.0293
```

```
The average loss for epoch 3 is loss :1.0657333135604858, val loss : 0.9559950232505798
```

```
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```
Epoch 4 Loss 1.065733
```

```
Time taken for 1 epoch 129.73010969161987 sec
```

```
Epoch 5 Batch 0 Loss 1.0390
```

```
Epoch 5 Batch 100 Loss 0.9046
```

```
Epoch 5 Batch 200 Loss 0.9192
```

```
The average loss for epoch 4 is loss :0.9864731431007385, val loss : 0.8736454248428345
```

```
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```
Epoch 5 Loss 0.986473
```

```
Time taken for 1 epoch 129.73555541038513 sec
```

```
Epoch 6 Batch 0 Loss 0.8591
```

```
Epoch 6 Batch 100 Loss 0.8884
```

```
Epoch 6 Batch 200 Loss 0.8643
```

```
The average loss for epoch 5 is loss :0.9139974117279053, val loss : 0.7982656359672546
```

```
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```

Epoch 6 Loss 0.913997

Time taken for 1 epoch 133.85419583320618 sec

Epoch 7 Batch 0 Loss 0.7831

Epoch 7 Batch 100 Loss 0.8224

Epoch 7 Batch 200 Loss 0.7251

The average loss for epoch 6 is loss :0.8464154005050659, val loss : 0.7465582489967346

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Epoch 7 Loss 0.846415

Time taken for 1 epoch 132.5537531375885 sec

Epoch 8 Batch 0 Loss 0.7638

Epoch 8 Batch 100 Loss 0.7533

Epoch 8 Batch 200 Loss 0.7683

The average loss for epoch 7 is loss :0.7868040204048157, val loss : 0.6876528859138489

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Epoch 8 Loss 0.786804

Time taken for 1 epoch 131.92531085014343 sec

Epoch 9 Batch 0 Loss 0.7548

Epoch 9 Batch 100 Loss 0.7553

Epoch 9 Batch 200 Loss 0.7525

The average loss for epoch 8 is loss :0.7314950823783875, val loss : 0.6310684084892273

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Epoch 9 Loss 0.731495

Time taken for 1 epoch 133.68691897392273 sec

Epoch 10 Batch 0 Loss 0.7262

Epoch 10 Batch 100 Loss 0.6377

Epoch 10 Batch 200 Loss 0.7258

The average loss for epoch 9 is loss :0.6818535923957825, val loss : 0.58516925573349

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Epoch 10 Loss 0.681854

Time taken for 1 epoch 133.8631489276886 sec

Epoch 11 Batch 0 Loss 0.6390

Epoch 11 Batch 100 Loss 0.6017

Epoch 11 Batch 200 Loss 0.6221

The average loss for epoch 10 is loss :0.6390568614006042, val loss : 0.5414778590202332

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Epoch 11 Loss 0.639057

Time taken for 1 epoch 134.92159986495972 sec

Epoch 12 Batch 0 Loss 0.5389

Epoch 12 Batch 100 Loss 0.5626

Epoch 12 Batch 200 Loss 0.5809

The average loss for epoch 11 is loss :0.5961672067642212, val loss : 0.49637743830680847

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Epoch 12 Loss 0.596167

Time taken for 1 epoch 131.5539038181305 sec

Epoch 13 Batch 0 Loss 0.4670

Epoch 13 Batch 100 Loss 0.5736

Epoch 13 Batch 200 Loss 0.5834

The average loss for epoch 12 is loss :0.554612398147583, val loss : 0.4531552195549011

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

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Epoch 13 Loss 0.554612

Time taken for 1 epoch 131.56400227546692 sec

Epoch 14 Batch 0 Loss 0.4553

Epoch 14 Batch 100 Loss 0.4760

Epoch 14 Batch 200 Loss 0.5401

The average loss for epoch 13 is loss :0.5173757076263428, val loss : 0.43149736523628235

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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf/assets
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```
Epoch 14 Loss 0.517376
```

```
Time taken for 1 epoch 131.0647840499878 sec
```

```
Epoch 15 Batch 0 Loss 0.4001
```

```
Epoch 15 Batch 100 Loss 0.4585
```

```
Epoch 15 Batch 200 Loss 0.6045
```

```
The average loss for epoch 14 is loss :0.4817495048046112, val loss : 0.39942580461502075
```

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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf/assets
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```
Epoch 15 Loss 0.481750
```

```
Time taken for 1 epoch 133.80771112442017 sec
```

```
Epoch 16 Batch 0 Loss 0.4260
```

```
Epoch 16 Batch 100 Loss 0.4201
```

```
Epoch 16 Batch 200 Loss 0.5502
```

```
The average loss for epoch 15 is loss :0.4478289783000946, val loss : 0.36567163467407227
```

```
INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf/assets
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```
Epoch 16 Loss 0.447829
```

```
Time taken for 1 epoch 129.64232349395752 sec
```

```
Epoch 17 Batch 0 Loss 0.4747
```

```
Epoch 17 Batch 100 Loss 0.4007
```

```
Epoch 17 Batch 200 Loss 0.4438
```

```
The average loss for epoch 16 is loss :0.42073220014572144, val loss : 0.3377225399017334
```

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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets
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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf/assets
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Epoch 17 Loss 0.420732

Time taken for 1 epoch 126.04263734817505 sec

Epoch 18 Batch 0 Loss 0.3691

Epoch 18 Batch 100 Loss 0.3839

Epoch 18 Batch 200 Loss 0.4473

The average loss for epoch 17 is loss :0.39178651571273804, val loss : 0.3112975060939789

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets

WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

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Epoch 18 Loss 0.391787

Time taken for 1 epoch 120.16709923744202 sec

Epoch 19 Batch 0 Loss 0.2745

Epoch 19 Batch 100 Loss 0.3771

Epoch 19 Batch 200 Loss 0.3905

The average loss for epoch 18 is loss :0.3696826696395874, val loss : 0.2964300811290741

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf/assets

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Epoch 19 Loss 0.369683

Time taken for 1 epoch 119.59282851219177 sec

Epoch 20 Batch 0 Loss 0.3262

Epoch 20 Batch 100 Loss 0.3862

Epoch 20 Batch 200 Loss 0.3939

The average loss for epoch 19 is loss :0.3474860191345215, val loss : 0.2792894244194031

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

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Epoch 20 Loss 0.347486

Time taken for 1 epoch 118.32523846626282 sec

Epoch 21 Batch 0 Loss 0.3189

Epoch 21 Batch 100 Loss 0.3207

Epoch 21 Batch 200 Loss 0.3711

The average loss for epoch 20 is loss :0.32754597067832947, val loss : 0.2548556625843048

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf/assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

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Epoch 21 Loss 0.327546

Time taken for 1 epoch 118.27027940750122 sec

Epoch 22 Batch 0 Loss 0.2324

Epoch 22 Batch 100 Loss 0.2978

Epoch 22 Batch 200 Loss 0.3271

The average loss for epoch 21 is loss :0.3102485239505768, val loss : 0.24257387220859528

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

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Epoch 22 Loss 0.310249

Time taken for 1 epoch 119.69194269180298 sec

Epoch 23 Batch 0 Loss 0.2290

Epoch 23 Batch 100 Loss 0.2775

Epoch 23 Batch 200 Loss 0.2781

The average loss for epoch 22 is loss :0.295152485370636, val loss : 0.22846055030822754

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

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Epoch 23 Loss 0.295152

Time taken for 1 epoch 119.60317730903625 sec

Epoch 24 Batch 0 Loss 0.2452

Epoch 24 Batch 100 Loss 0.2579

Epoch 24 Batch 200 Loss 0.3281

The average loss for epoch 23 is loss :0.28552505373954773, val loss : 0.22802652418613434

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

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Epoch 24 Loss 0.285525

Time taken for 1 epoch 118.26145219802856 sec

Epoch 25 Batch 0 Loss 0.2344

Epoch 25 Batch 100 Loss 0.2714

Epoch 25 Batch 200 Loss 0.3318

The average loss for epoch 24 is loss :0.27038413286209106, val loss : 0.21523161232471466

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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets
WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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```
Epoch 25 Loss 0.270384
```

```
Time taken for 1 epoch 118.58765244483948 sec
```

```
Epoch 26 Batch 0 Loss 0.2394
```

```
Epoch 26 Batch 100 Loss 0.2338
```

```
Epoch 26 Batch 200 Loss 0.2852
```

```
The average loss for epoch 25 is loss :0.2597709894180298, val loss : 0.21243613958358765
```

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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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```
Epoch 26 Loss 0.259771
```

```
Time taken for 1 epoch 120.57104825973511 sec
```

```
Epoch 27 Batch 0 Loss 0.2302
```

```
Epoch 27 Batch 100 Loss 0.2332
```

```
Epoch 27 Batch 200 Loss 0.2840
```

```
The average loss for epoch 26 is loss :0.250794380903244, val loss : 0.19864805042743683
```

```
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets
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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets
```

```
Epoch 27 Loss 0.250794
```

```
Time taken for 1 epoch 150.63693165779114 sec
```

```
Epoch 28 Batch 0 Loss 0.1831
```

```
Epoch 28 Batch 100 Loss 0.2620
```

```
Epoch 28 Batch 200 Loss 0.2475
```

```
The average loss for epoch 27 is loss :0.2392662614583969, val loss : 0.19143107533454895
```

```
INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets
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WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.
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INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets
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Epoch 28 Loss 0.239266

Time taken for 1 epoch 149.00134253501892 sec

Epoch 29 Batch 0 Loss 0.1891

Epoch 29 Batch 100 Loss 0.2246

Epoch 29 Batch 200 Loss 0.2687

The average loss for epoch 28 is loss :0.2330838143825531, val loss : 0.18441535532474518

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

Epoch 29 Loss 0.233084

Time taken for 1 epoch 147.64659309387207 sec

Epoch 30 Batch 0 Loss 0.1807

Epoch 30 Batch 100 Loss 0.2051

Epoch 30 Batch 200 Loss 0.2516

The average loss for epoch 29 is loss :0.22710320353507996, val loss : 0.17915289103984833

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/encoder.tf\assets

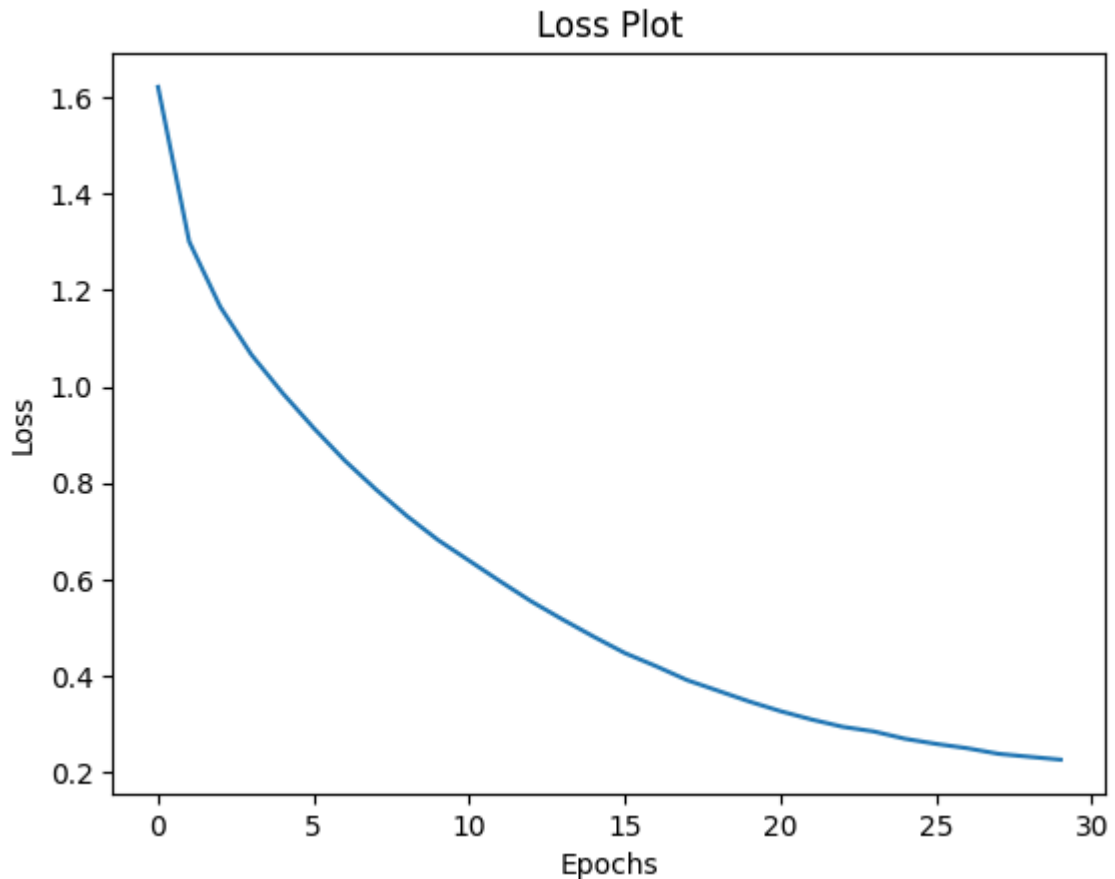
WARNING:absl:Found untraced functions such as gru_cell_layer_call_fn, gru_cell_layer_call_and_return_conditional_losses while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

INFO:tensorflow:Assets written to: ./models/25_4_2024_22h20/decoder.tf\assets

Epoch 30 Loss 0.227103

Time taken for 1 epoch 156.79484629631042 sec



display the trained model's results

fonctions d'évaluation visuelle:

```
In [ ]: def evaluate(image):
    attention_plot = np.zeros((max_length, attention_features_shape))

    hidden = decoder.reset_state(batch_size=1)

    temp_input = tf.expand_dims(load_image(image)[0], 0)
    img_tensor_val = image_features_extract_model(temp_input)
    img_tensor_val = tf.reshape(img_tensor_val, (img_tensor_val.shape[0], -1, img_tensor_val.shape[-1]))

    features = encoder(img_tensor_val)

    dec_input = tf.expand_dims([tokenizer.word_index['<start>']], 0)
    result = []

    for i in range(max_length):
        predictions, hidden, attention_weights = decoder(dec_input, features, hidden)

        attention_plot[i] = tf.reshape(attention_weights, (-1, )).numpy()

        # Reshape predictions to be a 2D matrix of shape [batch_size, vocab_size]
        predictions = tf.reshape(predictions, [1, -1])

        predicted_id = tf.random.categorical(predictions, 1)[0][0].numpy()
        result.append(tokenizer.index_word[predicted_id])

        if tokenizer.index_word[predicted_id] == '<end>':
```

```

        return result, attention_plot

    dec_input = tf.expand_dims([predicted_id], 0)

    attention_plot = attention_plot[:len(result), :]
    return result, attention_plot

# Fonction permettant la représentation de l'attention au niveau de l'image
def plot_attention(image, result, attention_plot):
    temp_image = np.array(Image.open(image))

    fig = plt.figure(figsize=(10, 10))

    len_result = len(result)
    for l in range(len_result):
        temp_att = np.resize(attention_plot[l], (8, 8))
        ax = fig.add_subplot(len_result//2, len_result//2, l+1)
        ax.set_title(result[l])
        img = ax.imshow(temp_image)
        ax.imshow(temp_att, cmap='gray', alpha=0.6, extent=img.get_extent())

    plt.tight_layout()
    plt.show()

```

Lancement des fonctions avec une image du jeu de validation

```

In [ ]: # Affichage de quelques annotations dans le jeu de test
rid = np.random.randint(0, len(img_name_val))
image = img_name_val[rid]
print(image)
real_caption = ' '.join([tokenizer.index_word[i] for i in cap_val[rid] if i not
result, attention_plot = evaluate(image)

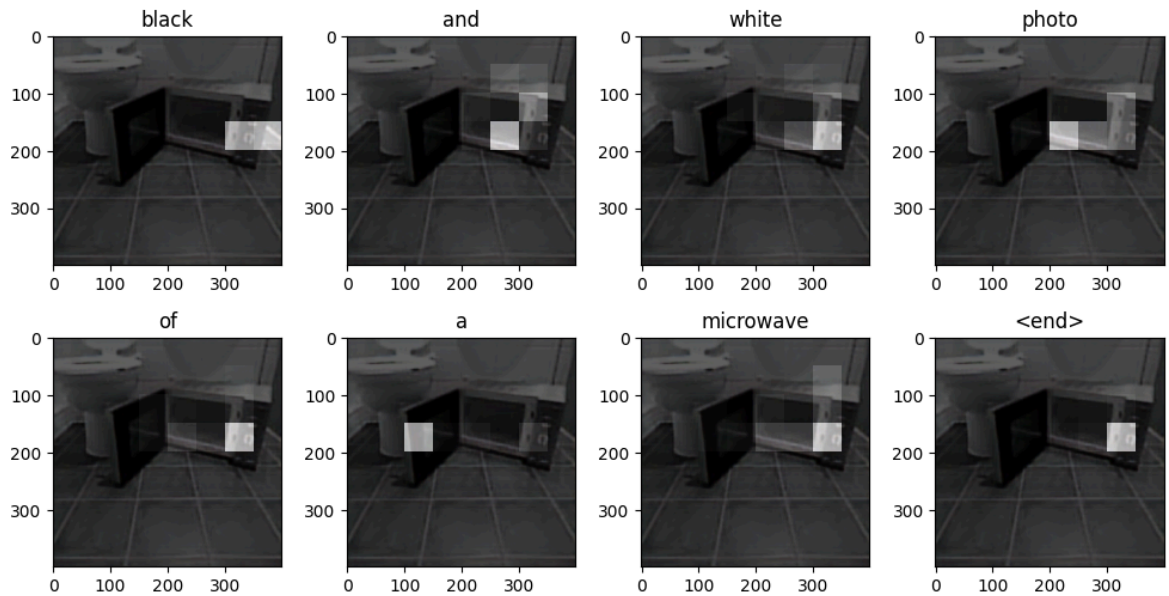
print ('Real Caption:', real_caption)
print ('Prediction Caption:', ' '.join(result))
plot_attention(image, result, attention_plot)

```

d:\CESI\A5\datascience\Projet\DataScience\Livrable_3\denoised_train2014\COCO_train2014_000000085452.jpg

Real Caption: <start> a microwave oven with its door open sits on the bathroom floor next to the commode <end>

Prediction Caption: black and white photo of a microwave <end>



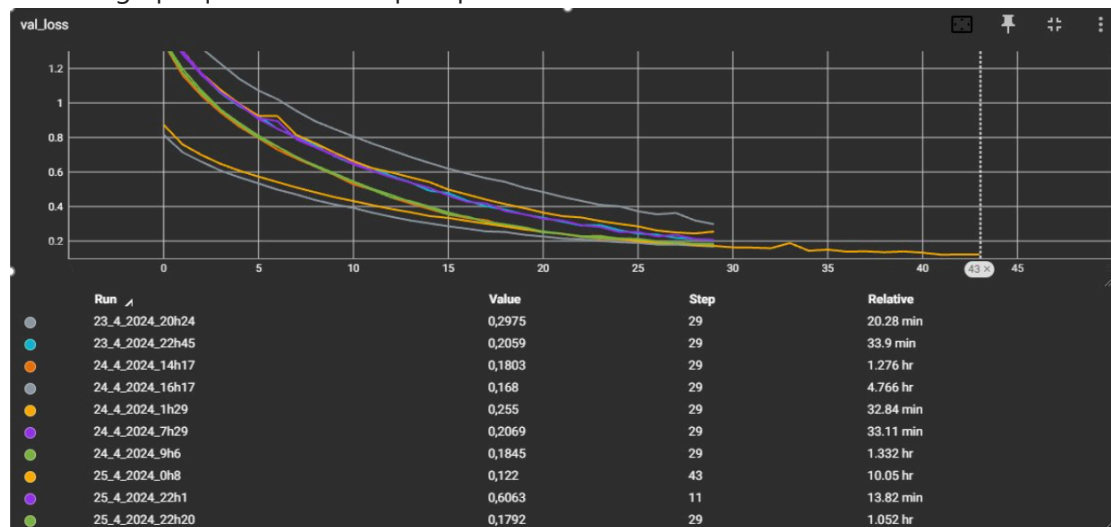
Sélection du meilleur modèle

Grâce à nos callbacks, Nous pouvons avoir l'évolution de nos entrainements de manière visuelle a l'aide de tensorboard.

Ainsi, nous avons réalisé plusieurs entrainements, avec différents paramètres. Nous avons modifiés:

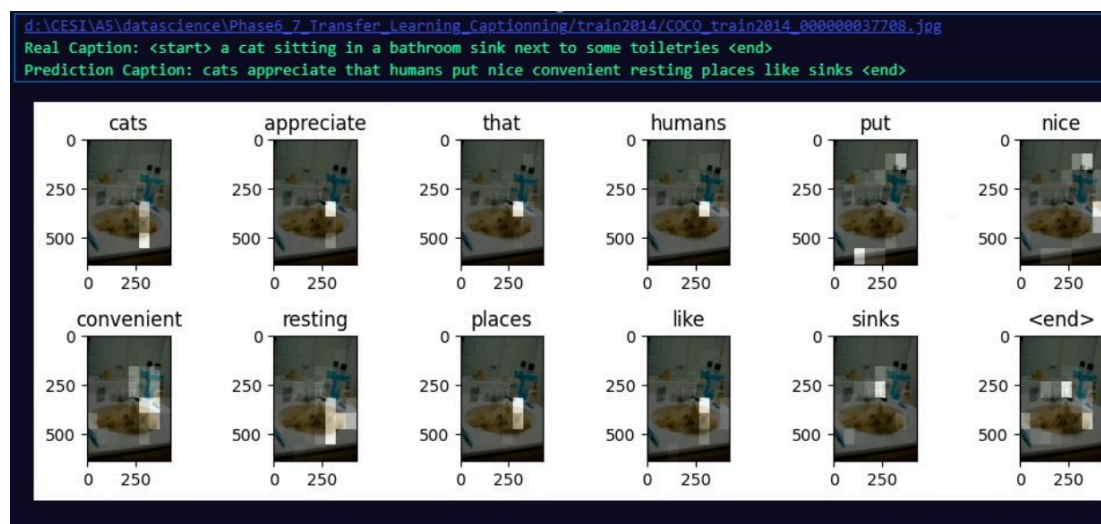
- Le batch size, pour changer la fréquence d'apprentissage dans l'epoch
- La learning rate pour modifier la vitesse d'apprentissage a chaque apprentissage
- Le buffer size
- Le nombre d'image lors de l'entrainement pour avoir plus d'exemple (multiplie le temps d'entrainement)

Voici un graphique de nos loss par epoch sur nos différents entrainements



La loss que nous avons pris ne suffisait pas a maximiser les résultats, mais elle donnait un bon indicateur sur la pertinences des termes choisis.

Voici un exemple d'excellent caption obtenu par notre modèle sur le jeu de test(c'est une photo avec un chat dans un évier).



Problèmes rencontrés et améliorations

Après sélection d'un modèle performant, en essayant de faire la pipeline globale du projet avec les 3 modèles, le débruitage du modèle de denoising c'était du flou (car on perdait un peu d'infos avec les convolutions). Ainsi le modèle voyait uniquement du flou, il a fallu refaire l'entraînement avec un dataset de photos dénoisés.

Nous pouvons améliorer la qualité des captions générés en prenant en compte une autre loss, la loss Blue (keras_nlp.metrics.Blue).

Conclusion

Nous avons donc notre modèle capable de générer un caption à partir d'images.

Nous n'avons plus qu'à emboîter nos modèles pour faire notre pipeline finale pour ce projet.