Image Captioning

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Description: Implement an image captioning model using a CNN and a Transformer.

Setup

```
import os
import re
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.applications import efficientnet
from tensorflow.keras.layers import TextVectorization


seed = 111
np.random.seed(seed)
tf.random.set_seed(seed)
```

Download the dataset

We will be using the Flickr8K dataset for this tutorial. This dataset comprises over 8,000 images, that are each paired with five different captions.

```
!wget -q https://github.com/jbrownlee/Datasets/releases/download/Flickr8k/Flickr8k_Dataset.zip
!wget -q https://github.com/jbrownlee/Datasets/releases/download/Flickr8k/Flickr8k_text.zip
!unzip -qq Flickr8k_Dataset.zip
!unzip -qq Flickr8k_text.zip
!rm Flickr8k_Dataset.zip Flickr8k_text.zip
```

```

# Path to the images
IMAGES_PATH = "Flicker8k_Dataset"

# Desired image dimensions
```

```
IMAGE_SIZE = (299, 299)

# Vocabulary size
VOCAB_SIZE = 10000

# Fixed length allowed for any sequence
SEQ_LENGTH = 25

# Dimension for the image embeddings and token embeddings
EMBED_DIM = 512

# Per-layer units in the feed-forward network
FF_DIM = 512

# Other training parameters
BATCH_SIZE = 64
EPOCHS = 10
AUTOTUNE = tf.data.AUTOTUNE
```

Preparing the dataset

```
def load_captions_data(filename):
    """Loads captions (text) data and maps them to corresponding images.

    Args:
        filename: Path to the text file containing caption data.

    Returns:
        caption_mapping: Dictionary mapping image names and the corresponding captions
        text_data: List containing all the available captions
    """

    with open(filename) as caption_file:
        caption_data = caption_file.readlines()
        caption_mapping = {}
        text_data = []
        images_to_skip = set()

        for line in caption_data:
            line = line.rstrip("\n")
            # Image name and captions are separated using a tab
            img_name, caption = line.split("\t")

            # Each image is repeated five times for the five different captions.
            # Each image name has a suffix `#(caption_number)`
            img_name = img_name.split("#")[0]
            img_name = os.path.join(IMAGES_PATH, img_name.strip())

            # We will remove caption that are either too short to too long
            tokens = caption.strip().split()

            if len(tokens) < 5 or len(tokens) > SEQ_LENGTH:
                images_to_skip.add(img_name)
```

```
                continue

            if img_name.endswith("jpg") and img_name not in images_to_skip:
                # We will add a start and an end token to each caption
                caption = "<start> " + caption.strip() + " <end>"
                text_data.append(caption)

                if img_name in caption_mapping:
                    caption_mapping[img_name].append(caption)
                else:
                    caption_mapping[img_name] = [caption]

        for img_name in images_to_skip:
            if img_name in caption_mapping:
                del caption_mapping[img_name]

        return caption_mapping, text_data


def train_val_split(caption_data, train_size=0.8, shuffle=True):
    """Split the captioning dataset into train and validation sets.

    Args:
        caption_data (dict): Dictionary containing the mapped caption data
        train_size (float): Fraction of all the full dataset to use as training data
        shuffle (bool): Whether to shuffle the dataset before splitting

    Returns:
        Traning and validation datasets as two separated dicts
    """

    # 1. Get the list of all image names
    all_images = list(caption_data.keys())

    # 2. Shuffle if necessary
    if shuffle:
        np.random.shuffle(all_images)

    # 3. Split into training and validation sets
    train_size = int(len(caption_data) * train_size)

    training_data = {
        img_name: caption_data[img_name] for img_name in all_images[:train_size]
    }
    validation_data = {
        img_name: caption_data[img_name] for img_name in all_images[train_size:]
    }

    # 4. Return the splits
    return training_data, validation_data


# Load the dataset
captions_mapping, text_data = load_captions_data("Flickr8k.token.txt")

# Split the dataset into training and validation sets
```

```
train_data, valid_data = train_val_split(captions_mapping)
print("Number of training samples: ", len(train_data))
print("Number of validation samples: ", len(valid_data))
```

```
Number of training samples:  6114
Number of validation samples:  1529
```

Vectorizing the text data

We'll use the `TextVectorization` layer to vectorize the text data, that is to say, to turn the original strings into integer sequences where each integer represents the index of a word in a vocabulary. We will use a custom string standardization scheme (strip punctuation characters except `<` and `>`) and the default splitting scheme (split on whitespace).

```
def custom_standardization(input_string):
    lowercase = tf.strings.lower(input_string)
    return tf.strings.regex_replace(lowercase, "[%s]" % re.escape(strip_chars), "")


strip_chars = "!\"#$%&'()*+,-./:;<=>?@[\]^_`{|}~"
strip_chars = strip_chars.replace("<", "")
strip_chars = strip_chars.replace(">", "")

vectorization = TextVectorization(
    max_tokens=VOCAB_SIZE,
    output_mode="int",
    output_sequence_length=SEQ_LENGTH,
    standardize=custom_standardization,
)
vectorization.adapt(text_data)

# Data augmentation for image data
image_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.2),
        layers.RandomContrast(0.3),
    ]
)
```

Building a `tf.data.Dataset` pipeline for training

We will generate pairs of images and corresponding captions using a `tf.data.Dataset` object. The pipeline consists of two steps:

1. Read the image from the disk
2. Tokenize all the five captions corresponding to the image

```
def decode_and_resize(img_path):
```

```
    img = tf.io.read_file(img_path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, IMAGE_SIZE)
    img = tf.image.convert_image_dtype(img, tf.float32)
    return img


def process_input(img_path, captions):
    return decode_and_resize(img_path), vectorization(captions)


def make_dataset(images, captions):
    dataset = tf.data.Dataset.from_tensor_slices((images, captions))
    dataset = dataset.shuffle(BATCH_SIZE * 8)
    dataset = dataset.map(process_input, num_parallel_calls=AUTOTUNE)
    dataset = dataset.batch(BATCH_SIZE).prefetch(AUTOTUNE)

    return dataset


# Pass the list of images and the list of corresponding captions
train_dataset = make_dataset(list(train_data.keys()), list(train_data.values()))

valid_dataset = make_dataset(list(valid_data.keys()), list(valid_data.values()))
```

Building the model

Our image captioning architecture consists of three models:

1. A CNN: used to extract the image features
2. A TransformerEncoder: The extracted image features are then passed to a Transformer

```
             based encoder that generates a new representation of the inputs
```

3. A TransformerDecoder: This model takes the encoder output and the text data

```
             (sequences) as inputs and tries to learn to generate the caption.
```

```
def get_cnn_model():
    base_model = efficientnet.EfficientNetB0(
        input_shape=(*IMAGE_SIZE, 3), include_top=False, weights="imagenet",
    )
    # We freeze our feature extractor
    base_model.trainable = False
    base_model_out = base_model.output
    base_model_out = layers.Reshape((-1, base_model_out.shape[-1]))(base_model_out)
    cnn_model = keras.models.Model(base_model.input, base_model_out)
    return cnn_model
```

```python
class TransformerEncoderBlock(layers.Layer):
    def __init__(self, embed_dim, dense_dim, num_heads, **kwargs):
        super().__init__(**kwargs)
        self.embed_dim = embed_dim
        self.dense_dim = dense_dim
        self.num_heads = num_heads
        self.attention_1 = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim, dropout=0.0
        )
        self.layernorm_1 = layers.LayerNormalization()
        self.layernorm_2 = layers.LayerNormalization()
        self.dense_1 = layers.Dense(embed_dim, activation="relu")

    def call(self, inputs, training, mask=None):
        inputs = self.layernorm_1(inputs)
        inputs = self.dense_1(inputs)

        attention_output_1 = self.attention_1(
            query=inputs,
            value=inputs,
            key=inputs,
            attention_mask=None,
            training=training,
        )
        out_1 = self.layernorm_2(inputs + attention_output_1)
        return out_1


class PositionalEmbedding(layers.Layer):
    def __init__(self, sequence_length, vocab_size, embed_dim, **kwargs):
        super().__init__(**kwargs)
        self.token_embeddings = layers.Embedding(
            input_dim=vocab_size, output_dim=embed_dim
        )
        self.position_embeddings = layers.Embedding(
            input_dim=sequence_length, output_dim=embed_dim
        )
        self.sequence_length = sequence_length
        self.vocab_size = vocab_size
        self.embed_dim = embed_dim
        self.embed_scale = tf.math.sqrt(tf.cast(embed_dim, tf.float32))

    def call(self, inputs):
        length = tf.shape(inputs)[-1]
        positions = tf.range(start=0, limit=length, delta=1)
        embedded_tokens = self.token_embeddings(inputs)
        embedded_tokens = embedded_tokens * self.embed_scale
        embedded_positions = self.position_embeddings(positions)
        return embedded_tokens + embedded_positions

    def compute_mask(self, inputs, mask=None):
        return tf.math.not_equal(inputs, 0)
```

```
class TransformerDecoderBlock(layers.Layer):
    def __init__(self, embed_dim, ff_dim, num_heads, **kwargs):
        super().__init__(**kwargs)
        self.embed_dim = embed_dim
        self.ff_dim = ff_dim
        self.num_heads = num_heads
        self.attention_1 = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim, dropout=0.1
        )
        self.attention_2 = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim, dropout=0.1
        )
        self.ffn_layer_1 = layers.Dense(ff_dim, activation="relu")
        self.ffn_layer_2 = layers.Dense(embed_dim)

        self.layernorm_1 = layers.LayerNormalization()
        self.layernorm_2 = layers.LayerNormalization()
        self.layernorm_3 = layers.LayerNormalization()

        self.embedding = PositionalEmbedding(
            embed_dim=EMBED_DIM, sequence_length=SEQ_LENGTH, vocab_size=VOCAB_SIZE
        )
        self.out = layers.Dense(VOCAB_SIZE, activation="softmax")

        self.dropout_1 = layers.Dropout(0.3)
        self.dropout_2 = layers.Dropout(0.5)
        self.supports_masking = True

    def call(self, inputs, encoder_outputs, training, mask=None):
        inputs = self.embedding(inputs)
        causal_mask = self.get_causal_attention_mask(inputs)

        if mask is not None:
            padding_mask = tf.cast(mask[:, :, tf.newaxis], dtype=tf.int32)
            combined_mask = tf.cast(mask[:, tf.newaxis, :], dtype=tf.int32)
            combined_mask = tf.minimum(combined_mask, causal_mask)

        attention_output_1 = self.attention_1(
            query=inputs,
            value=inputs,
            key=inputs,
            attention_mask=combined_mask,
            training=training,
        )
        out_1 = self.layernorm_1(inputs + attention_output_1)

        attention_output_2 = self.attention_2(
            query=out_1,
            value=encoder_outputs,
            key=encoder_outputs,
            attention_mask=padding_mask,
            training=training,
        )
        out_2 = self.layernorm_2(out_1 + attention_output_2)

        ffn_out = self.ffn_layer_1(out_2)
```

```
        ffn_out = self.dropout_1(ffn_out, training=training)
        ffn_out = self.ffn_layer_2(ffn_out)

        ffn_out = self.layernorm_3(ffn_out + out_2, training=training)
        ffn_out = self.dropout_2(ffn_out, training=training)
        preds = self.out(ffn_out)
        return preds

    def get_causal_attention_mask(self, inputs):
        input_shape = tf.shape(inputs)
        batch_size, sequence_length = input_shape[0], input_shape[1]
        i = tf.range(sequence_length)[:, tf.newaxis]
        j = tf.range(sequence_length)
        mask = tf.cast(i >= j, dtype="int32")
        mask = tf.reshape(mask, (1, input_shape[1], input_shape[1]))
        mult = tf.concat(
            [tf.expand_dims(batch_size, -1), tf.constant([1, 1], dtype=tf.int32)],
            axis=0,
        )
        return tf.tile(mask, mult)


class ImageCaptioningModel(keras.Model):
    def __init__(
        self, cnn_model, encoder, decoder, num_captions_per_image=5, image_aug=None,
    ):
        super().__init__()
        self.cnn_model = cnn_model
        self.encoder = encoder
        self.decoder = decoder
        self.loss_tracker = keras.metrics.Mean(name="loss")
        self.acc_tracker = keras.metrics.Mean(name="accuracy")
        self.num_captions_per_image = num_captions_per_image
        self.image_aug = image_aug

    def calculate_loss(self, y_true, y_pred, mask):
        loss = self.loss(y_true, y_pred)
        mask = tf.cast(mask, dtype=loss.dtype)
        loss *= mask
        return tf.reduce_sum(loss) / tf.reduce_sum(mask)

    def calculate_accuracy(self, y_true, y_pred, mask):
        accuracy = tf.equal(y_true, tf.argmax(y_pred, axis=2))
        accuracy = tf.math.logical_and(mask, accuracy)
        accuracy = tf.cast(accuracy, dtype=tf.float32)
        mask = tf.cast(mask, dtype=tf.float32)
        return tf.reduce_sum(accuracy) / tf.reduce_sum(mask)

    def _compute_caption_loss_and_acc(self, img_embed, batch_seq, training=True):
        encoder_out = self.encoder(img_embed, training=training)
        batch_seq_inp = batch_seq[:, :-1]
        batch_seq_true = batch_seq[:, 1:]
        mask = tf.math.not_equal(batch_seq_true, 0)
        batch_seq_pred = self.decoder(
            batch_seq_inp, encoder_out, training=training, mask=mask
        )
```

```
        loss = self.calculate_loss(batch_seq_true, batch_seq_pred, mask)
        acc = self.calculate_accuracy(batch_seq_true, batch_seq_pred, mask)
        return loss, acc

    def train_step(self, batch_data):
        batch_img, batch_seq = batch_data
        batch_loss = 0
        batch_acc = 0

        if self.image_aug:
            batch_img = self.image_aug(batch_img)

        # 1. Get image embeddings
        img_embed = self.cnn_model(batch_img)

        # 2. Pass each of the five captions one by one to the decoder
        # along with the encoder outputs and compute the loss as well as accuracy
        # for each caption.
        for i in range(self.num_captions_per_image):
            with tf.GradientTape() as tape:
                loss, acc = self._compute_caption_loss_and_acc(
                    img_embed, batch_seq[:, i, :], training=True
                )

                # 3. Update loss and accuracy
                batch_loss += loss
                batch_acc += acc

            # 4. Get the list of all the trainable weights
            train_vars = (
                self.encoder.trainable_variables + self.decoder.trainable_variables
            )

            # 5. Get the gradients
            grads = tape.gradient(loss, train_vars)

            # 6. Update the trainable weights
            self.optimizer.apply_gradients(zip(grads, train_vars))

        # 7. Update the trackers
        batch_acc /= float(self.num_captions_per_image)
        self.loss_tracker.update_state(batch_loss)
        self.acc_tracker.update_state(batch_acc)

        # 8. Return the loss and accuracy values
        return {"loss": self.loss_tracker.result(), "acc": self.acc_tracker.result()}

    def test_step(self, batch_data):
        batch_img, batch_seq = batch_data
        batch_loss = 0
        batch_acc = 0

        # 1. Get image embeddings
        img_embed = self.cnn_model(batch_img)

        # 2. Pass each of the five captions one by one to the decoder
```

```
        # along with the encoder outputs and compute the loss as well as accuracy
        # for each caption.
        for i in range(self.num_captions_per_image):
            loss, acc = self._compute_caption_loss_and_acc(
                img_embed, batch_seq[:, i, :], training=False
            )

            # 3. Update batch loss and batch accuracy
            batch_loss += loss
            batch_acc += acc

        batch_acc /= float(self.num_captions_per_image)

        # 4. Update the trackers
        self.loss_tracker.update_state(batch_loss)
        self.acc_tracker.update_state(batch_acc)

        # 5. Return the loss and accuracy values
        return {"loss": self.loss_tracker.result(), "acc": self.acc_tracker.result()}

    @property
    def metrics(self):
        # We need to list our metrics here so the `reset_states()` can be
        # called automatically.
        return [self.loss_tracker, self.acc_tracker]


cnn_model = get_cnn_model()
encoder = TransformerEncoderBlock(embed_dim=EMBED_DIM, dense_dim=FF_DIM, num_heads=1)
decoder = TransformerDecoderBlock(embed_dim=EMBED_DIM, ff_dim=FF_DIM, num_heads=2)
caption_model = ImageCaptioningModel(
    cnn_model=cnn_model, encoder=encoder, decoder=decoder, image_aug=image_augmentation,
)
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb0_notop.h5
16705208/16705208 [==============================] - 0s 0us/step
```

Model training

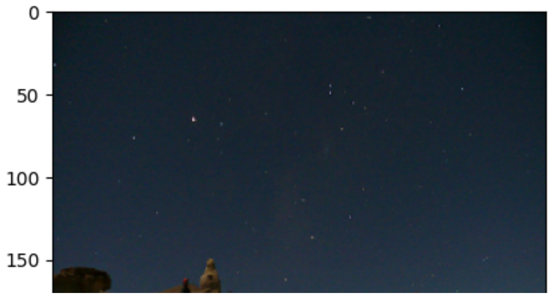
```
# Define the loss function
cross_entropy = keras.losses.SparseCategoricalCrossentropy(
    from_logits=False, reduction="none"
)

# EarlyStopping criteria
early_stopping = keras.callbacks.EarlyStopping(patience=3, restore_best_weights=True)


# Learning Rate Scheduler for the optimizer
class LRSchedule(keras.optimizers.schedules.LearningRateSchedule):
    def __init__(self, post_warmup_learning_rate, warmup_steps):
        super().__init__()
        self.post_warmup_learning_rate = post_warmup_learning_rate
```

```
        self.warmup_steps = warmup_steps

    def __call__(self, step):
        global_step = tf.cast(step, tf.float32)
        warmup_steps = tf.cast(self.warmup_steps, tf.float32)
        warmup_progress = global_step / warmup_steps
        warmup_learning_rate = self.post_warmup_learning_rate * warmup_progress
        return tf.cond(
            global_step < warmup_steps,
            lambda: warmup_learning_rate,
            lambda: self.post_warmup_learning_rate,
        )


# Create a learning rate schedule
num_train_steps = len(train_dataset) * EPOCHS
num_warmup_steps = num_train_steps // 15
lr_schedule = LRSchedule(post_warmup_learning_rate=1e-4, warmup_steps=num_warmup_steps)

# Compile the model
caption_model.compile(optimizer=keras.optimizers.Adam(lr_schedule), loss=cross_entropy)

# Fit the model
caption_model.fit(
    train_dataset,
    epochs=EPOCHS,
    validation_data=valid_dataset,
    callbacks=[early_stopping],
)
```

```
Epoch 1/10
96/96 [==============================] - 115s 891ms/step - loss: 25.8875 - acc: 0.1626 - val_loss: 19.8587 - val_acc: 0.3221
Epoch 2/10
96/96 [==============================] - 72s 746ms/step - loss: 18.9614 - acc: 0.3287 - val_loss: 17.7379 - val_acc: 0.3563
Epoch 3/10
96/96 [==============================] - 70s 727ms/step - loss: 17.2337 - acc: 0.3590 - val_loss: 16.7830 - val_acc: 0.3706
Epoch 4/10
96/96 [==============================] - 72s 745ms/step - loss: 16.1897 - acc: 0.3772 - val_loss: 16.1433 - val_acc: 0.3821
Epoch 5/10
96/96 [==============================] - 73s 761ms/step - loss: 15.4063 - acc: 0.3917 - val_loss: 15.7774 - val_acc: 0.3915
Epoch 6/10
96/96 [==============================] - 69s 723ms/step - loss: 14.7617 - acc: 0.4042 - val_loss: 15.4436 - val_acc: 0.3988
Epoch 7/10
96/96 [==============================] - 70s 731ms/step - loss: 14.2460 - acc: 0.4152 - val_loss: 15.2994 - val_acc: 0.4015
Epoch 8/10
96/96 [==============================] - 70s 729ms/step - loss: 13.7740 - acc: 0.4243 - val_loss: 15.1418 - val_acc: 0.4062
Epoch 9/10
96/96 [==============================] - 70s 733ms/step - loss: 13.3694 - acc: 0.4336 - val_loss: 15.0823 - val_acc: 0.4088
Epoch 10/10
96/96 [==============================] - 70s 730ms/step - loss: 12.9892 - acc: 0.4429 - val_loss: 14.9590 - val_acc: 0.4100
<keras.src.callbacks.History at 0x7fbc93495c90>
```

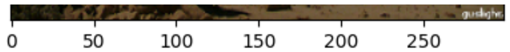
Check sample predictions

```python
vocab = vectorization.get_vocabulary()
index_lookup = dict(zip(range(len(vocab)), vocab))
max_decoded_sentence_length = SEQ_LENGTH - 1
valid_images = list(valid_data.keys())


def generate_caption():
    # Select a random image from the validation dataset
    sample_img = np.random.choice(valid_images)

    # Read the image from the disk
    sample_img = decode_and_resize(sample_img)
    img = sample_img.numpy().clip(0, 255).astype(np.uint8)
    plt.imshow(img)
    plt.show()

    # Pass the image to the CNN
    img = tf.expand_dims(sample_img, 0)
    img = caption_model.cnn_model(img)

    # Pass the image features to the Transformer encoder
    encoded_img = caption_model.encoder(img, training=False)

    # Generate the caption using the Transformer decoder
    decoded_caption = "<start> "
    for i in range(max_decoded_sentence_length):
        tokenized_caption = vectorization([decoded_caption])[:, :-1]
        mask = tf.math.not_equal(tokenized_caption, 0)
        predictions = caption_model.decoder(
            tokenized_caption, encoded_img, training=False, mask=mask
        )
        sampled_token_index = np.argmax(predictions[0, i, :])
        sampled_token = index_lookup[sampled_token_index]
        if sampled_token == "<end>":
            break
        decoded_caption += " " + sampled_token

    decoded_caption = decoded_caption.replace("<start> ", "")
    decoded_caption = decoded_caption.replace(" <end>", "").strip()
    print("Predicted Caption: ", decoded_caption)


# Check predictions for a few samples
generate_caption()
```



End Notes

We saw that the model starts to generate reasonable captions after a few epochs. To keep this example easily runnable, we have trained it with a few constraints, like a minimal number of attention heads. To improve the predictions, you can try changing these training settings and find a good model for your use case.




```
Predicted Caption:  a man is standing on a rocky beach
```