Image Captioning

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

Setup

In [1]:
```
import os

os.environ["KERAS_BACKEND"] = "tensorflow"

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

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

keras.utils.set_random_seed(111)
```

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.

In [2]:
```
!wget -q https://github.com/jbrownlee/Datasets/releases/download/Flickr8k/Flickr8k_Dat
!wget -q https://github.com/jbrownlee/Datasets/releases/download/Flickr8k/Flickr8k_tex
!unzip -qq Flickr8k_Dataset.zip
!unzip -qq Flickr8k_text.zip
!rm Flickr8k_Dataset.zip Flickr8k_text.zip
```

In [3]:
```
# 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 = 30
AUTOTUNE = tf.data.AUTOTUNE
```

Preparing the dataset

In [4]:
```
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]
```

```python
        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).

In [5]:
```python
def custom_standardization(input_string):
    lowercase = tf.strings.lower(input_string)
```

```python
    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

In [6]:

```python
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.`

In [7]:
```
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


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
```

```python
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)
```

```python
        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/efficientnetb
0_notop.h5
16705208/16705208 [==============================] - 0s 0us/step
```

Model training

In [12]:

```
# 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 1/30
96/96 [==============================] - 124s 950ms/step - loss: 28.0877 - acc: 0.131
1 - val_loss: 20.4179 - val_acc: 0.3116
Epoch 2/30
96/96 [==============================] - 73s 759ms/step - loss: 19.3218 - acc: 0.3208
- val_loss: 17.9316 - val_acc: 0.3544
Epoch 3/30
96/96 [==============================] - 72s 747ms/step - loss: 17.4338 - acc: 0.3552
- val_loss: 16.8776 - val_acc: 0.3699
Epoch 4/30
96/96 [==============================] - 72s 744ms/step - loss: 16.3173 - acc: 0.3751
- val_loss: 16.2088 - val_acc: 0.3820
Epoch 5/30
96/96 [==============================] - 71s 742ms/step - loss: 15.5225 - acc: 0.3894
- val_loss: 15.7903 - val_acc: 0.3914
Epoch 6/30
96/96 [==============================] - 72s 747ms/step - loss: 14.8448 - acc: 0.4014
- val_loss: 15.4643 - val_acc: 0.3978
Epoch 7/30
96/96 [==============================] - 72s 745ms/step - loss: 14.3130 - acc: 0.4141
- val_loss: 15.2643 - val_acc: 0.4022
Epoch 8/30
96/96 [==============================] - 72s 747ms/step - loss: 13.8544 - acc: 0.4227
- val_loss: 15.1261 - val_acc: 0.4086
Epoch 9/30
96/96 [==============================] - 72s 747ms/step - loss: 13.4164 - acc: 0.4336
- val_loss: 15.0295 - val_acc: 0.4101
Epoch 10/30
96/96 [==============================] - 72s 746ms/step - loss: 13.0486 - acc: 0.4412
- val_loss: 14.9031 - val_acc: 0.4119
Epoch 11/30
96/96 [==============================] - 71s 744ms/step - loss: 12.6893 - acc: 0.4493
- val_loss: 14.9374 - val_acc: 0.4137
Epoch 12/30
96/96 [==============================] - 71s 741ms/step - loss: 12.3630 - acc: 0.4562
- val_loss: 14.9302 - val_acc: 0.4127
Epoch 13/30
96/96 [==============================] - 72s 745ms/step - loss: 12.0576 - acc: 0.4639
- val_loss: 14.8459 - val_acc: 0.4153
Epoch 14/30
96/96 [==============================] - 71s 744ms/step - loss: 11.7722 - acc: 0.4707
- val_loss: 14.8965 - val_acc: 0.4157
Epoch 15/30
96/96 [==============================] - 71s 738ms/step - loss: 11.5078 - acc: 0.4783
- val_loss: 14.9239 - val_acc: 0.4151
Epoch 16/30
96/96 [==============================] - 72s 746ms/step - loss: 11.2436 - acc: 0.4851
- val_loss: 14.9561 - val_acc: 0.4151
```

Out[12]:

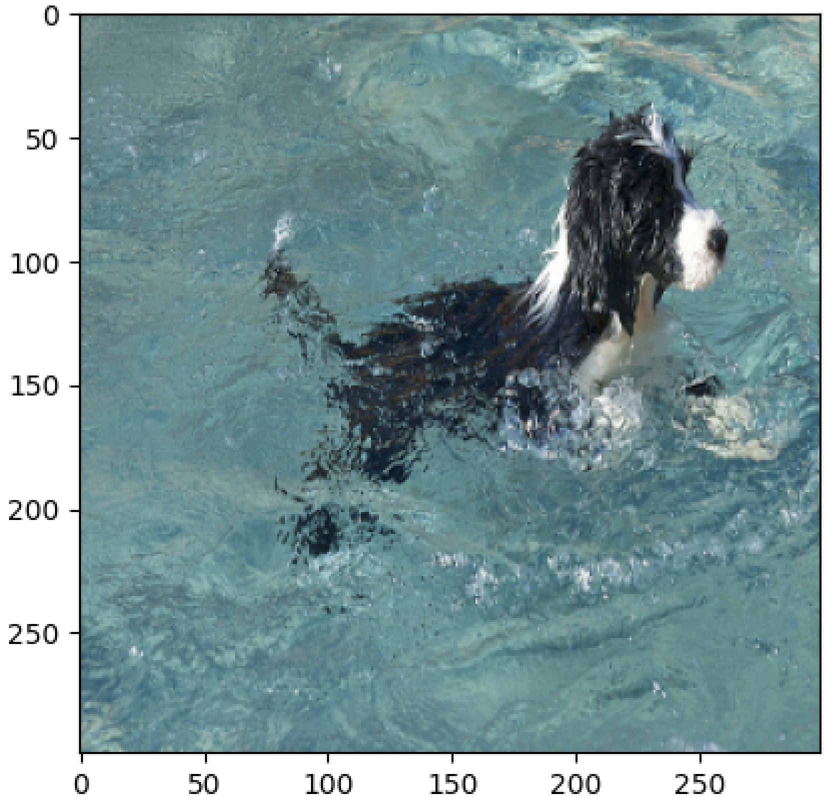
```
<keras.src.callbacks.History at 0x7f94e958c310>
```

Check sample predictions

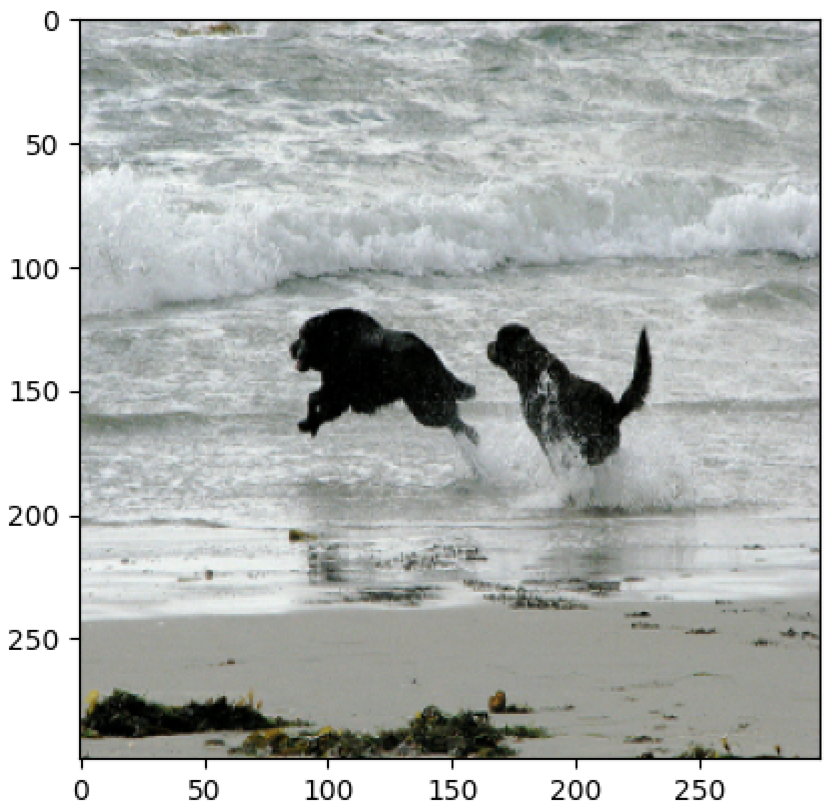
In [13]:

```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())
```

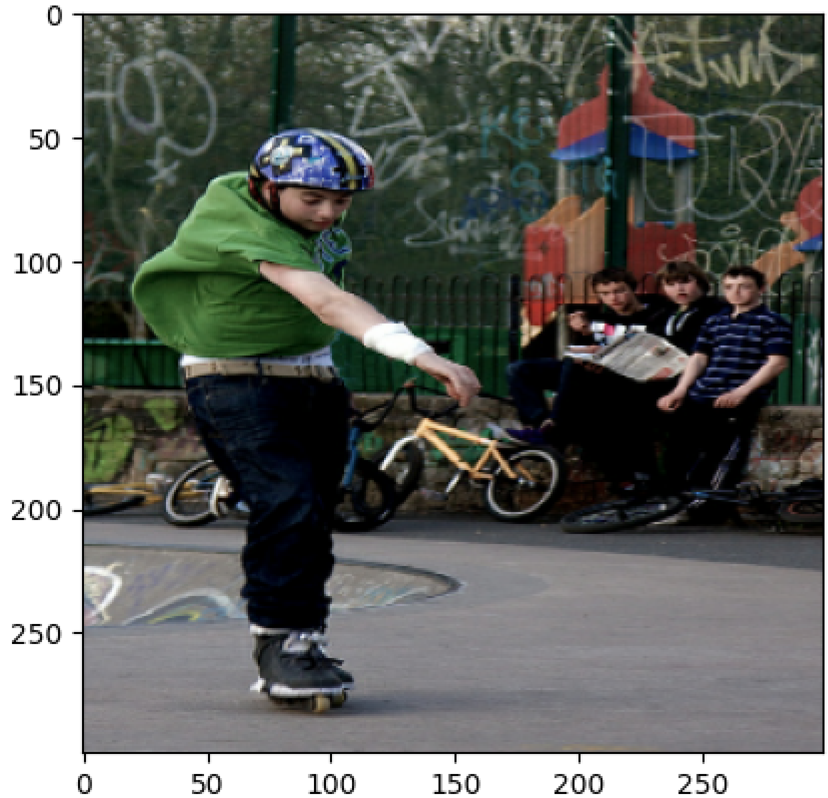
```python
def generate_caption():
    # Select a random image from the validation dataset
    sample_img = np.random.choice(valid_images)

    # 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()
generate_caption()
generate_caption()
```



Predicted Caption: a black and white dog swimming in the water



Predicted Caption: a black dog running through the ocean



```
Predicted Caption:  a man wearing a helmet and helmet riding a unicycle
```

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.

```
In [ ]:
```