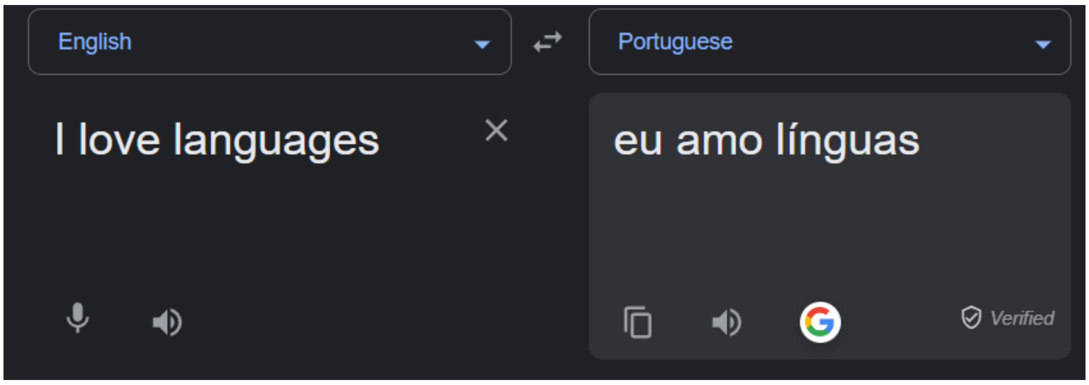
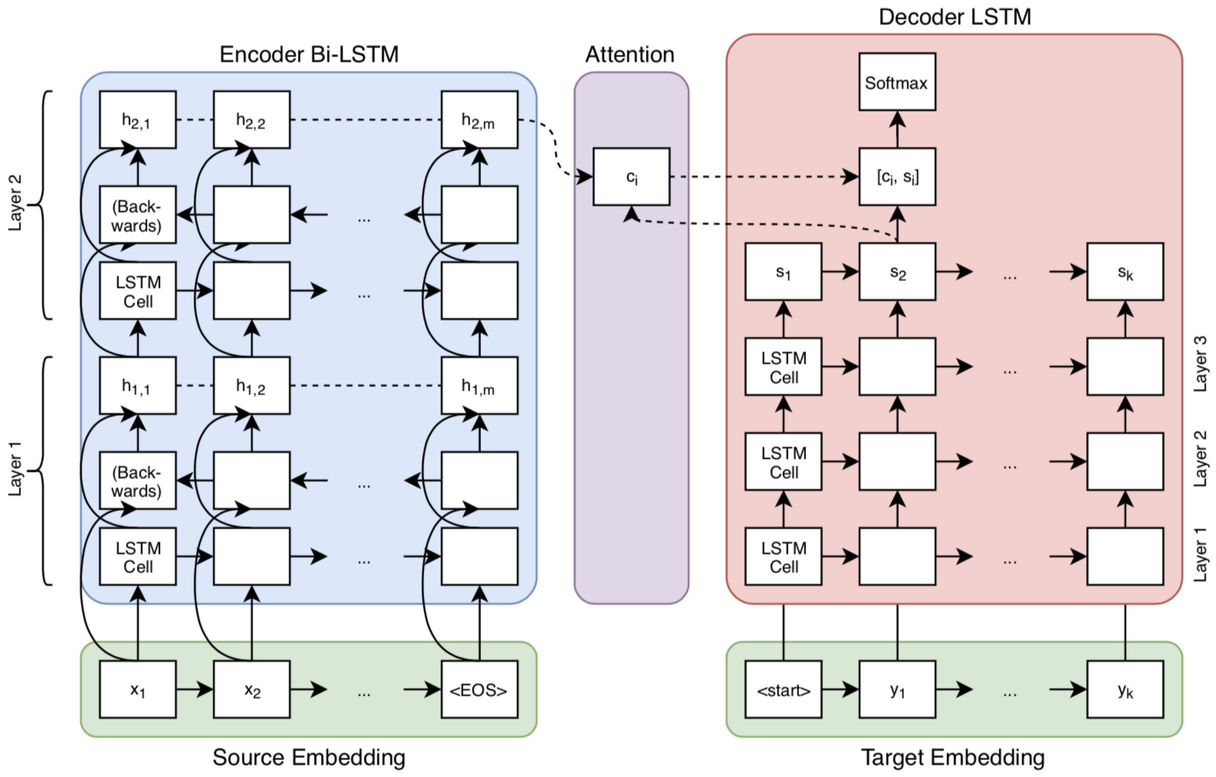
Neural Machine Translation (English-Portuguese)



I love languages

eu amo línguas



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Neural Machine Translation

We will build an English-to-Portuguese neural machine translation (NMT) model using Long Short-Term Memory (LSTM) networks with attention. Machine translation is an important task in natural language processing and could be useful not only for translating one language to another but also for word sense disambiguation (e.g. determining whether the word "bank" refers to the financial bank, or the land alongside a river). Implementing this using just a Recurrent Neural Network (RNN) with LSTMs can work for short to medium length sentences but can result in vanishing gradients for very long sequences. To help with this, we will be adding an attention mechanism to allow the decoder to access all relevant parts of the input sentence regardless of its length, we will:

- Implement an encoder-decoder system with attention
- Build the NMT model from scratch using Tensorflow
- Generate translations using greedy and Minimum Bayes Risk (MBR) decoding

In [ ]:
```
#! pip install tensorflow_text
```

In [ ]:
```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3' # Setting this env variable prevents TF warnings from showing up

import numpy as np
import tensorflow as tf
from collections import Counter
import tensorflow as tf
import tensorflow_text as tf_text
import pathlib
```

1. Data Preparation

The steps performed for text pre-processing can be summarized as:

- Reading the raw data from the text files
- Cleaning the data (using lowercase, adding space around punctuation, trimming whitespaces, etc)
- Splitting it into training and validation sets
- Adding the start-of-sentence and end-of-sentence tokens to every sentence
- Tokenizing the sentences
- Creating a Tensorflow dataset out of the tokenized sentences

Take a moment to inspect the raw sentences:

In [ ]:
```
def load_data(path):
    text = path.read_text(encoding="utf-8")

    lines = text.splitlines()
    pairs = [line.split("\t") for line in lines]

    context = np.array([context for target, context, _ in pairs])
    target = np.array([target for target, context, _ in pairs])

    return context, target
```

In [ ]:
```
path_to_file = pathlib.Path("por.txt")
```

In [ ]:
```
portuguese_sentences, english_sentences = load_data(path_to_file)
```

In [ ]:
```
BUFFER_SIZE = len(english_sentences)
BATCH_SIZE = 64

is_train = np.random.uniform(size=(len(portuguese_sentences),)) < 0.8

train_raw = (
    tf.data.Dataset.from_tensor_slices(
        (english_sentences[is_train], portuguese_sentences[is_train])
    )
    .shuffle(BUFFER_SIZE)
    .batch(BATCH_SIZE)
)
val_raw = (
    tf.data.Dataset.from_tensor_slices(
        (english_sentences[~is_train], portuguese_sentences[~is_train])
    )
    .shuffle(BUFFER_SIZE)
    .batch(BATCH_SIZE)
)
```

In [ ]:
```
def tf_lower_and_split_punct(text):
    text = tf_text.normalize_utf8(text, "NFKD")
    text = tf.strings.lower(text)
    text = tf.strings.regex_replace(text, "[^ a-z.?!,¿]", "")
    text = tf.strings.regex_replace(text, "[.?!,¿]", r" \0 ")
    text = tf.strings.strip(text)
    text = tf.strings.join(["[SOS]", text, "[EOS]"], separator=" ")
    return text


max_vocab_size = 12000

english_vectorizer = tf.keras.layers.TextVectorization(
    standardize=tf_lower_and_split_punct, max_tokens=max_vocab_size, ragged=True
)

english_vectorizer.adapt(train_raw.map(lambda context, target: context))

portuguese_vectorizer = tf.keras.layers.TextVectorization(
    standardize=tf_lower_and_split_punct, max_tokens=max_vocab_size, ragged=True
)

portuguese_vectorizer.adapt(train_raw.map(lambda context, target: target))
```

In [ ]:
```
def process_text(context, target):
    context = english_vectorizer(context).to_tensor()
    target = portuguese_vectorizer(target)
    targ_in = target[:, :-1].to_tensor()
    targ_out = target[:, 1:].to_tensor()
    return (context, targ_in), targ_out


train_data = train_raw.map(process_text, tf.data.AUTOTUNE)
val_data = val_raw.map(process_text, tf.data.AUTOTUNE)
```

Quick test

In [ ]:
```
print(f"English (to translate) sentence:\n\n{english_sentences[-5]}\n")
print(f"Portuguese (translation) sentence:\n\n{portuguese_sentences[-5]}")
```

```
English (to translate) sentence:

No matter how much you try to convince people that chocolate is vanilla, it'll still be chocolate, even though
you may manage to convince yourself and a few others that it's vanilla.

Portuguese (translation) sentence:

Não importa o quanto você tenta convencer os outros de que chocolate é baunilha, ele ainda será chocolate, mesm
o que você possa convencer a si mesmo e poucos outros de que é baunilha.
```

We don't have much use for the raw sentences so delete them to save memory:

In [ ]:
```
del portuguese_sentences
del english_sentences
```

In [ ]:
```
print(f"First 10 words of the english vocabulary:\n\n{english_vectorizer.get_vocabulary()[:10]}\n")
print(f"First 10 words of the portuguese vocabulary:\n\n{portuguese_vectorizer.get_vocabulary()[:10]}")
```

```
First 10 words of the english vocabulary:

['', '[UNK]', '[SOS]', '[EOS]', '.', 'tom', 'i', 'to', 'you', 'the']

First 10 words of the portuguese vocabulary:

['', '[UNK]', '[SOS]', '[EOS]', '.', 'tom', 'que', 'o', 'nao', 'eu']
```

Notice that the first 4 words are reserved for special words. In order, these are:

- the empty string
- a special token to represent an unknown word
- a special token to represent the start of a sentence
- a special token to represent the end of a sentence

We can see how many words are in a vocabulary by using the `vocabulary_size` method:

In [ ]:
```
# Size of the vocabulary
vocab_size = portuguese_vectorizer.vocabulary_size()

print(f"Portuguese vocabulary is made up of {vocab_size} words")
```

```
Portuguese vocabulary is made up of 12000 words
```

We can define tf.keras.layers.StringLookup objects that will help us map from words to ids and vice versa. Do this for the portuguese vocabulary since this will be useful later on when we decode the predictions from Our model:

In [ ]:
```
# This helps us convert from words to ids
```

```python
# This helps us convert from words to ids
word_to_id = tf.keras.layers.StringLookup(
    vocabulary=portuguese_vectorizer.get_vocabulary(),
    mask_token="",
    oov_token="[UNK]"
)

# This helps us convert from ids to words
id_to_word = tf.keras.layers.StringLookup(
    vocabulary=portuguese_vectorizer.get_vocabulary(),
    mask_token="",
    oov_token="[UNK]",
    invert=True,
)
```

Try it out for the special tokens and a random word:

In [ ]:
```python
unk_id = word_to_id("[UNK]")
sos_id = word_to_id("[SOS]")
eos_id = word_to_id("[EOS]")
baunilha_id = word_to_id("baunilha")

print(f"The id for the [UNK] token is {unk_id}")
print(f"The id for the [SOS] token is {sos_id}")
print(f"The id for the [EOS] token is {eos_id}")
print(f"The id for baunilha (vanilla) is {baunilha_id}")
```

```
The id for the [UNK] token is 1
The id for the [SOS] token is 2
The id for the [EOS] token is 3
The id for baunilha (vanilla) is 7049
```

Finally take a look at how the data that is going to be fed to the neural network looks like. Both `train_data` and `val_data` are of type `tf.data.Dataset` and are already arranged in batches of 64 examples. To get the first batch out of a tf dataset you can use the `take` method. To get the first example out of the batch you can slice the tensor and use the `numpy` method for nicer printing:

In [ ]:
```python
for (to_translate, sr_translation), translation in train_data.take(1):
    print(f"Tokenized english sentence:\n{to_translate[0, :].numpy()}\n\n")
    print(f"Tokenized portuguese sentence (shifted to the right):\n{sr_translation[0, :].numpy()}\n\n")
    print(f"Tokenized portuguese sentence:\n{translation[0, :].numpy()}\n\n")
```

```
Tokenized english sentence:
[  2   6 164   8 248 154 294   4   3   0   0   0   0   0   0   0   0   0
   0]


Tokenized portuguese sentence (shifted to the right):
[   2    9  151    6   14   26 2376  112  431    4    0    0    0    0
    0    0]


Tokenized portuguese sentence:
[   9  151    6   14   26 2376  112  431    4    3    0    0    0    0
    0    0]
```

2. NMT model with attention

The model we will build uses an encoder-decoder architecture. This Recurrent Neural Network (RNN) takes in a tokenized version of a sentence in its encoder, then passes it on to the decoder for translation. Using a a regular sequence-to-sequence model with LSTMs will work effectively for short to medium sentences but will start to degrade for longer ones. We can picture it as all of the context of the input sentence is compressed into one vector that is passed into the decoder block. this will be an issue for very long sentences (e.g. 100 tokens or more) because the context of the first parts of the input will have very little effect on the final vector passed to the decoder.

Adding an attention layer to this model avoids this problem by giving the decoder access to all parts of the input sentence.

There are different ways to implement attention and the one we'll use for this Notebook is the Scaled Dot Product Attention which has the form:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$
We can think of it as computing scores using queries (Q) and keys (K), followed by a multiplication of values (V) to get a context vector at a particular timestep of the decoder. This context vector is fed to the decoder RNN to get a set of probabilities for the next predicted word. The division by square root of the keys dimensionality ($\sqrt{d_k}$) is for improving model performance. For our machine translation application, the encoder activations (i.e. encoder hidden states) will be the keys and values, while the decoder activations (i.e. decoder hidden states) will be the queries.

We will see in the upcoming sections that this complex architecture and mechanism can be implemented with just a few lines of code.

First you will define two important global variables:

- The size of the vocabulary
- The number of units in the LSTM layers (the same number will be used for all LSTM layers)

In [ ]:
```
VOCAB_SIZE = 12000
UNITS = 256
```

1 - Encoder

Our first step is to code the encoder part of the neural network. We will create an `Encoder` class. Notice that in the constructor (the `__init__` method) we need to define all of the sublayers of the encoder and then use these sublayers during the forward pass (the `call` method).

The encoder consists of the following layers:

- Embedding. For this layer we need to define the appropriate `input_dim` and `output_dim` and let it know that you are using '0' as padding, which can be done by using the appropriate value for the `mask_zero` parameter.

- Bidirectional LSTM. In TF you can implement bidirectional behaviour for RNN-like layers. This part is already taken care of but we will need to specify the appropriate type of layer as well as its parameters. In particular we need to set the appropriate number of units and make sure that the LSTM returns the full sequence and not only the last output, which can be done by using the appropriate value for the `return_sequences` parameter.

We need to define the forward pass using the syntax of TF's functional API.

In [ ]:
```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, vocab_size, units):
        """Initializes an instance of this class

        Args:
            vocab_size (int): Size of the vocabulary
            units (int): Number of units in the LSTM layer
        """
        super(Encoder, self).__init__()

        self.embedding = tf.keras.layers.Embedding(
            input_dim=vocab_size,
            output_dim=units,
            mask_zero=True
        )

        self.rnn = tf.keras.layers.Bidirectional(
            merge_mode="sum",
            layer=tf.keras.layers.LSTM(
                units=units,
                return_sequences=True
            ),
        )


    def call(self, context):
        """Forward pass of this layer

        Args:
            context (tf.Tensor): The sentence to translate

        Returns:
            tf.Tensor: Encoded sentence to translate
        """
        # Pass the context through the embedding layer
        x = self.embedding(context)

        # Pass the output of the embedding through the RNN
        x = self.rnn(x)

        return x
```

In [ ]:
```
# Do a quick check of our implementation

# Create an instance of your class

encoder = Encoder(VOCAB_SIZE, UNITS)

# Pass a batch of sentences to translate from english to portuguese
encoder_output = encoder(to_translate)

print(f'Tensor of sentences in english has shape: {to_translate.shape}\n')
print(f'Encoder output has shape: {encoder_output.shape}')
```

```
Tensor of sentences in english has shape: (64, 19)

Encoder output has shape: (64, 19, 256)
```

2 - CrossAttention

Next step is to code the layer that will perform cross attention between the original sentences and the translations. For this, lets code the `CrossAttention` class below. Notice that in the constructor (the `__init__` method) we need to define all of the sublayers and then use these sublayers during the forward pass (the `call` method).

The cross attention consists of the following layers:

- MultiHeadAttention. For this layer we need to define the appropriate `key_dim`, which is the size of the key and query tensors. We will also need to set the number of heads to 1 since you aren't implementing multi head attention but attention between two tensors. The reason why this layer is preferred over Attention is that it allows simpler code during the forward pass.

A couple of things to notice:

- We need a way to pass both the output of the attention alongside the shifted-to-the-right translation (since this cross attention happens in the decoder side). For this we will use an Add layer so that the original dimension is preserved, which would not happen if you use something like a Concatenate layer.
- Layer normalization is also performed for better stability of the network by using a LayerNormalization layer.

In [ ]:
```python
# GRADED CLASS: CrossAttention
class CrossAttention(tf.keras.layers.Layer):
    def __init__(self, units):
        """Initializes an instance of this class

        Args:
            units (int): Number of units in the LSTM layer
        """
        super().__init__()

        self.mha = (
            tf.keras.layers.MultiHeadAttention(
                key_dim=units,
                num_heads=1
            )
        )



        self.layernorm = tf.keras.layers.LayerNormalization()
        self.add = tf.keras.layers.Add()

    def call(self, context, target):
        """Forward pass of this layer

        Args:
            context (tf.Tensor): Encoded sentence to translate
            target (tf.Tensor): The embedded shifted-to-the-right translation

        Returns:
            tf.Tensor: Cross attention between context and target
        """


        # Call the MH attention by passing in the query and value
        # For this case the query should be the translation and the value the encoded sentence to translate
        # Hint: Check the call arguments of MultiHeadAttention in the docs
        attn_output = self.mha(
            query=target,
            value=context
        )


        x = self.add([target, attn_output])

        x = self.layernorm(x)

        return x
```

In [ ]:
```python
# Do a quick check of your implementation

# Create an instance of your class
attention_layer = CrossAttention(UNITS)

# The attention layer expects the embedded sr-translation and the context
# The context (encoder_output) is already embedded so you need to do this for sr_translation:
sr_translation_embed = tf.keras.layers.Embedding(VOCAB_SIZE, output_dim=UNITS, mask_zero=True)(sr_translation)

# Compute the cross attention
attention_result = attention_layer(encoder_output, sr_translation_embed)

print(f'Tensor of contexts has shape: {encoder_output.shape}')
print(f'Tensor of translations has shape: {sr_translation_embed.shape}')
print(f'Tensor of attention scores has shape: {attention_result.shape}')
```

```
Tensor of contexts has shape: (64, 19, 256)
Tensor of translations has shape: (64, 16, 256)
Tensor of attention scores has shape: (64, 16, 256)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/layer.py:847: UserWarning: Layer 'cross_attention_4' (
of type CrossAttention) was passed an input with a mask attached to it. However, this layer does not support ma
sking and will therefore destroy the mask information. Downstream layers will not see the mask.
  warnings.warn(
```

Exercise 3 - Decoder

Now we will implement the decoder part of the neural network completing the `Decoder` class.

The decoder consists of the following layers:

- Embedding. For this layer we need to define the appropriate `input_dim` and `output_dim` and let it know that we are using '0' as padding, which can be done by using the appropriate value for the `mask_zero` parameter.
- Pre-attention LSTM. Unlike in the encoder in which you used a Bidirectional LSTM, here we will use a vanilla LSTM. Don't forget to set the appropriate number of units and make sure that the LSTM returns the full sequence and not only the last output, which can be done by using the appropriate value for the `return_sequences` parameter.

It is very important that this layer returns the state since this will be needed for inference so make sure to set the `return_state` parameter accordingly. Notice that LSTM layers return state as a tuple of two tensors called `memory_state` and `carry_state`, **however these names have been changed to better reflect what you have seen in the lectures to `hidden_state` and `cell_state` respectively**.

- The attention layer that performs cross attention between the sentence to translate and the right-shifted translation. Here you need to use the `CrossAttention` layer you defined in the previous exercise.
- Post-attention LSTM. Another LSTM layer. For this one we don't need it to return the state.
- Finally a Dense layer. This one should have the same number of units as the size of the vocabulary since we expect it to compute the logits for every possible word in the vocabulary. Make sure to use a `logsoftmax` activation function for this one, which you can get as tf.nn.log_softmax.

In [ ]:
```
class Decoder(tf.keras.layers.Layer):
    def __init__(self, vocab_size, units):
        """Initializes an instance of this class

        Args:
            vocab_size (int): Size of the vocabulary
            units (int): Number of units in the LSTM layer
        """
        super(Decoder, self).__init__()

        # The embedding layer
        self.embedding = tf.keras.layers.Embedding(
            input_dim=vocab_size,
            output_dim=units,
            mask_zero=True
        )

        # The RNN before attention
        self.pre_attention_rnn = tf.keras.layers.LSTM(
            units=units,
            return_sequences=True,
            return_state=True
        )

        # The attention layer
        self.attention = CrossAttention(units)

        # The RNN after attention
        self.post_attention_rnn = tf.keras.layers.LSTM(
            units=units,
            return_sequences=True
        )

        # The dense layer with logsoftmax activation
        self.output_layer = tf.keras.layers.Dense(
            units=vocab_size,
            activation= tf.nn.log_softmax
        )


    def call(self, context, target, state=None, return_state=False):
        """Forward pass of this layer

        Args:
            context (tf.Tensor): Encoded sentence to translate
            target (tf.Tensor): The shifted-to-the-right translation
            state (list[tf.Tensor, tf.Tensor], optional): Hidden state of the pre-attention LSTM. Defaults to N
            return_state (bool, optional): If set to true return the hidden states of the LSTM. Defaults to Fal

        Returns:
            tf.Tensor: The log_softmax probabilities of predicting a particular token
        """


        # Get the embedding of the input
        x = self.embedding(target)

        # Pass the embedded input into the pre attention LSTM

        x, hidden_state, cell_state = self.pre_attention_rnn(x, initial_state=state)

        # Perform cross attention between the context and the output of the LSTM (in that order)
        x = self.attention(context, x)

        # Do a pass through the post attention LSTM
        x = self.post_attention_rnn(x)

        # Compute the logits
        logits = self.output_layer(x)


        if return_state:
            return logits, [hidden_state, cell_state]

        return logits
```

In [ ]:

```
# Do a quick check of your implementation

# Create an instance of your class
decoder = Decoder(VOCAB_SIZE, UNITS)

# Notice that you don't need the embedded version of sr_translation since this is done inside the class
logits = decoder(encoder_output, sr_translation)

print(f'Tensor of contexts has shape: {encoder_output.shape}')
print(f'Tensor of right-shifted translations has shape: {sr_translation.shape}')
print(f'Tensor of logits has shape: {logits.shape}')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/layer.py:847: UserWarning: Layer 'cross_attention_5' (
of type CrossAttention) was passed an input with a mask attached to it. However, this layer does not support ma
sking and will therefore destroy the mask information. Downstream layers will not see the mask.
  warnings.warn(
Tensor of contexts has shape: (64, 19, 256)
Tensor of right-shifted translations has shape: (64, 16)
Tensor of logits has shape: (64, 16, 12000)
/usr/local/lib/python3.10/dist-packages/keras/src/layers/layer.py:847: UserWarning: Layer 'decoder' (of type De
coder) was passed an input with a mask attached to it. However, this layer does not support masking and will th
erefore destroy the mask information. Downstream layers will not see the mask.
  warnings.warn(
```

4 - Translator

Now we have to put together all of the layers you previously coded into an actual model. For this, we'll code the `Translator` class below. Notice how unlike the Encoder and Decoder classes inherited from `tf.keras.layers.Layer`, the Translator class inherits from `tf.keras.layers.Model`.

Remember that `train_data` will yield a tuple with the sentence to translate and the shifted-to-the-right translation, which are the "features" of the model. This means that the inputs of your network will be tuples containing context and targets.

In [ ]:

```
class Translator(tf.keras.Model):
    def __init__(self, vocab_size, units):
        """Initializes an instance of this class

        Args:
            vocab_size (int): Size of the vocabulary
            units (int): Number of units in the LSTM layer
        """
        super().__init__()


        # Define the encoder with the appropriate vocab_size and number of units
        self.encoder = Encoder(vocab_size,units)

        # Define the decoder with the appropriate vocab_size and number of units
        self.decoder = Decoder(vocab_size,units)


    def call(self, inputs):
        """Forward pass of this layer

        Args:
            inputs (tuple(tf.Tensor, tf.Tensor)): Tuple containing the context (sentence to translate) and the

        Returns:
            tf.Tensor: The log_softmax probabilities of predicting a particular token
        """

        # In this case inputs is a tuple consisting of the context and the target, unpack it into single variab
        context, target = inputs

        # Pass the context through the encoder
        encoded_context = self.encoder(context)

        # Compute the logits by passing the encoded context and the target to the decoder
        logits = self.decoder(encoded_context,target)


        return logits
```

In [ ]:
```
# Do a quick check of your implementation

# Create an instance of your class
translator = Translator(VOCAB_SIZE, UNITS)

# Compute the logits for every word in the vocabulary
logits = translator((to_translate, sr_translation))

print(f'Tensor of sentences to translate has shape: {to_translate.shape}')
print(f'Tensor of right-shifted translations has shape: {sr_translation.shape}')
print(f'Tensor of logits has shape: {logits.shape}')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/layer.py:847: UserWarning: Layer 'cross_attention_6' (
of type CrossAttention) was passed an input with a mask attached to it. However, this layer does not support ma
sking and will therefore destroy the mask information. Downstream layers will not see the mask.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/keras/src/layers/layer.py:847: UserWarning: Layer 'decoder_1' (of type
Decoder) was passed an input with a mask attached to it. However, this layer does not support masking and will
therefore destroy the mask information. Downstream layers will not see the mask.
  warnings.warn(
Tensor of sentences to translate has shape: (64, 19)
Tensor of right-shifted translations has shape: (64, 16)
Tensor of logits has shape: (64, 16, 12000)
```

3. Training

Now that we have an untrained instance of the NMT model, it is time to train it. But first we need to define a `masked_loss` and a `masked_accuracy` functions, so that the padding doesn't affect the calculations of the loss and accuracy, then we can use the `compile_and_train` function below to achieve this:

In [ ]:
```
def masked_loss(y_true, y_pred):

    loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True, reduction='none')
    loss = loss_fn(y_true, y_pred)

    # Check which elements of y_true are padding
    mask = tf.cast(y_true != 0, loss.dtype)

    loss *= mask
    # Return the total.
    return tf.reduce_sum(loss)/tf.reduce_sum(mask)


def masked_acc(y_true, y_pred):
    y_pred = tf.argmax(y_pred, axis=-1)
    y_pred = tf.cast(y_pred, y_true.dtype)
    match = tf.cast(y_true == y_pred, tf.float32)
    mask = tf.cast(y_true != 0, tf.float32)

    return tf.reduce_sum(match)/tf.reduce_sum(mask)
```

In [ ]:
```
def compile_and_train(model, epochs=20, steps_per_epoch=500):
    model.compile(optimizer="adam", loss=masked_loss, metrics=[masked_acc, masked_loss])

    history = model.fit(
        train_data.repeat(),
        epochs=epochs,
        steps_per_epoch=steps_per_epoch,
        validation_data=val_data,
        validation_steps=50,
        callbacks=[tf.keras.callbacks.EarlyStopping(patience=3)],
    )

    return model, history
```

In [ ]:
```python
# Train the translator (this takes some minutes so feel free to take a break)

trained_translator, history = compile_and_train(translator)
```

```
Epoch 1/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 85s 152ms/step - loss: 5.7552 - masked_acc: 0.1618 - masked_loss: 5.7552 - val_los
s: 4.3079 - val_masked_acc: 0.3427 - val_masked_loss: 4.3079
Epoch 2/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 73s 147ms/step - loss: 3.9851 - masked_acc: 0.3895 - masked_loss: 3.9851 - val_los
s: 3.0193 - val_masked_acc: 0.5011 - val_masked_loss: 3.0193
Epoch 3/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 150ms/step - loss: 2.8443 - masked_acc: 0.5302 - masked_loss: 2.8443 - val_los
s: 2.3734 - val_masked_acc: 0.5917 - val_masked_loss: 2.3734
Epoch 4/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 74s 149ms/step - loss: 2.2932 - masked_acc: 0.6048 - masked_loss: 2.2932 - val_los
s: 1.9514 - val_masked_acc: 0.6508 - val_masked_loss: 1.9514
Epoch 5/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 151ms/step - loss: 1.9554 - masked_acc: 0.6554 - masked_loss: 1.9554 - val_los
s: 1.7434 - val_masked_acc: 0.6799 - val_masked_loss: 1.7434
Epoch 6/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 151ms/step - loss: 1.6577 - masked_acc: 0.6933 - masked_loss: 1.6577 - val_los
s: 1.5821 - val_masked_acc: 0.7086 - val_masked_loss: 1.5821
Epoch 7/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 73s 147ms/step - loss: 1.5414 - masked_acc: 0.7096 - masked_loss: 1.5414 - val_los
s: 1.5006 - val_masked_acc: 0.7157 - val_masked_loss: 1.5006
Epoch 8/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 150ms/step - loss: 1.4252 - masked_acc: 0.7258 - masked_loss: 1.4252 - val_los
s: 1.3958 - val_masked_acc: 0.7283 - val_masked_loss: 1.3958
Epoch 9/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 74s 148ms/step - loss: 1.3543 - masked_acc: 0.7351 - masked_loss: 1.3543 - val_los
s: 1.3035 - val_masked_acc: 0.7393 - val_masked_loss: 1.3035
Epoch 10/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 150ms/step - loss: 1.2491 - masked_acc: 0.7461 - masked_loss: 1.2491 - val_los
s: 1.2421 - val_masked_acc: 0.7512 - val_masked_loss: 1.2421
Epoch 11/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 150ms/step - loss: 1.1032 - masked_acc: 0.7655 - masked_loss: 1.1032 - val_los
s: 1.2064 - val_masked_acc: 0.7518 - val_masked_loss: 1.2064
Epoch 12/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 0s 146ms/step - loss: 1.0793 - masked_acc: 0.7686 - masked_loss: 1.0793
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data; interrupting training. Make sur
e that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use
the `.repeat()` function when building your dataset.
  self.gen.throw(typ, value, traceback)
500/500 ━━━━━━━━━━━━━━━━━━━━ 114s 228ms/step - loss: 1.0793 - masked_acc: 0.7686 - masked_loss: 1.0793 - val_lo
ss: 1.1615 - val_masked_acc: 0.7393 - val_masked_loss: 1.1615
Epoch 13/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 76s 152ms/step - loss: 1.0744 - masked_acc: 0.7686 - masked_loss: 1.0744 - val_los
s: 1.1619 - val_masked_acc: 0.7588 - val_masked_loss: 1.1619
Epoch 14/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 149ms/step - loss: 1.0416 - masked_acc: 0.7726 - masked_loss: 1.0416 - val_los
s: 1.0925 - val_masked_acc: 0.7628 - val_masked_loss: 1.0925
Epoch 15/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 76s 151ms/step - loss: 0.9593 - masked_acc: 0.7854 - masked_loss: 0.9593 - val_los
s: 1.1123 - val_masked_acc: 0.7668 - val_masked_loss: 1.1123
Epoch 16/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 151ms/step - loss: 0.8780 - masked_acc: 0.7961 - masked_loss: 0.8780 - val_los
s: 1.0528 - val_masked_acc: 0.7716 - val_masked_loss: 1.0528
Epoch 17/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 77s 153ms/step - loss: 0.8824 - masked_acc: 0.7945 - masked_loss: 0.8824 - val_los
s: 1.0502 - val_masked_acc: 0.7750 - val_masked_loss: 1.0502
Epoch 18/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 76s 152ms/step - loss: 0.8712 - masked_acc: 0.7972 - masked_loss: 0.8712 - val_los
s: 1.0246 - val_masked_acc: 0.7774 - val_masked_loss: 1.0246
Epoch 19/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 76s 152ms/step - loss: 0.8717 - masked_acc: 0.7973 - masked_loss: 0.8717 - val_los
s: 1.0077 - val_masked_acc: 0.7831 - val_masked_loss: 1.0077
Epoch 20/20
500/500 ━━━━━━━━━━━━━━━━━━━━ 75s 150ms/step - loss: 0.7691 - masked_acc: 0.8141 - masked_loss: 0.7691 - val_los
s: 1.0101 - val_masked_acc: 0.7818 - val_masked_loss: 1.0101
```

4. Using the model for inference

Now that our model is trained we can use it for inference. To help us with this the `generate_next_token` function is provided. Notice that this function is meant to be used inside a for-loop, so we feed to it the information of the previous step to generate the information of the next step. In particular, we need to keep track of the state of the pre-attention LSTM in the decoder and if we are done with the translation.

Also notice that a `temperature` variable is introduced which determines how to select the next token given the predicted logits:

In [ ]:
```python
def generate_next_token(decoder, context, next_token, done, state, temperature=0.0):
    """Generates the next token in the sequence

    Args:
        decoder (Decoder): The decoder
        context (tf.Tensor): Encoded sentence to translate
        next_token (tf.Tensor): The predicted next token
        done (bool): True if the translation is complete
        state (list[tf.Tensor, tf.Tensor]): Hidden states of the pre-attention LSTM layer
        temperature (float, optional): The temperature that controls the randomness of the predicted tokens. De

    Returns:
        tuple(tf.Tensor, np.float, list[tf.Tensor, tf.Tensor], bool): The next token, log prob of said token, h
    """
    # Get the logits and state from the decoder
    logits, state = decoder(context, next_token, state=state, return_state=True)

    # Trim the intermediate dimension
    logits = logits[:, -1, :]

    # If temp is 0 then next_token is the argmax of logits
    if temperature == 0.0:
        next_token = tf.argmax(logits, axis=-1)

    # If temp is not 0 then next_token is sampled out of logits
    else:
        logits = logits / temperature
        next_token = tf.random.categorical(logits, num_samples=1)

    # Trim dimensions of size 1
    logits = tf.squeeze(logits)
    next_token = tf.squeeze(next_token)

    # Get the logit of the selected next_token
    logit = logits[next_token].numpy()

    # Reshape to (1,1) since this is the expected shape for text encoded as TF tensors
    next_token = tf.reshape(next_token, shape=(1,1))

    # If next_token is End-of-Sentence token you are done
    if next_token == eos_id:
        done = True

    return next_token, logit, state, done
```

See how it works by running the following cell:

```
In [ ]: # PROCESS SENTENCE TO TRANSLATE AND ENCODE

# A sentence you wish to translate
eng_sentence = "I love languages"

# Convert it to a tensor
texts = tf.convert_to_tensor(eng_sentence)[tf.newaxis]

# Vectorize it and pass it through the encoder
context = english_vectorizer(texts).to_tensor()
context = encoder(context)

# SET STATE OF THE DECODER

# Next token is Start-of-Sentence since you are starting fresh
next_token = tf.fill((1,1), sos_id)

# Hidden and Cell states of the LSTM can be mocked using uniform samples
state = [tf.random.uniform((1, UNITS)), tf.random.uniform((1, UNITS))]

# You are not done until next token is EOS token
done = False

# Generate next token
next_token, logit, state, done = generate_next_token(decoder, context, next_token, done, state, temperature=0.5
print(f"Next token: {next_token}\nLogit: {logit:.4f}\nDone? {done}")
```

```
Next token: [[4474]]
Logit: -18.7384
Done? False
```

5 - translation

Now we can put everything together to translate a given sentence.we'll code the `translate` function below.

This function will take care of the following steps:

- Process the sentence to translate and encode it
- Set the initial state of the decoder
- Get predictions of the next token (starting with the \ token) for a maximum of iterations (in case the \ token is never returned)

- Return the translated text (as a string), the logit of the last iteration (this helps measure how certain was that the sequence was translated in its totality) and the translation in token format.

In [ ]:
```
def tokens_to_text(tokens, id_to_word):
    words = id_to_word(tokens)
    result = tf.strings.reduce_join(words, axis=-1, separator=" ")
    return result
```

In [ ]:
```
def translate(model, text, max_length=50, temperature=0.0):
    """Translate a given sentence from English to Portuguese

    Args:
        model (tf.keras.Model): The trained translator
        text (string): The sentence to translate
        max_length (int, optional): The maximum length of the translation. Defaults to 50.
        temperature (float, optional): The temperature that controls the randomness of the predicted tokens. De

    Returns:
        tuple(str, np.float, tf.Tensor): The translation, logit that predicted <EOS> token and the tokenized tr
    """
    # Lists to save tokens and logits
    tokens, logits = [], []

    # PROCESS THE SENTENCE TO TRANSLATE

    # Convert the original string into a tensor
    text = tf.convert_to_tensor(text)[tf.newaxis]

    # Vectorize the text using the correct vectorizer
    context =  english_vectorizer(text).to_tensor()

    # Get the encoded context (pass the context through the encoder)
    # Hint: Remember you can get the encoder by using model.encoder
    context = model.encoder(context)

    # INITIAL STATE OF THE DECODER

    # First token should be SOS token with shape (1,1)
    next_token = tf.fill((1, 1), sos_id)

    # Initial hidden and cell states should be tensors of zeros with shape (1, UNITS)
    state = [tf.zeros((1, UNITS)), tf.zeros((1, UNITS))]

    # You are done when you draw a EOS token as next token (initial state is False)
    done = False

    # Iterate for max_length iterations
    for i in range(max_length):

        # Generate the next token
        next_token, logit, state, done = generate_next_token(
            decoder=model.decoder,
            context=context,
            next_token=next_token,
            done=done,
            state=state,
            temperature=temperature
        )

        # If done then break out of the loop
        if done:
            break

        # Add next_token to the list of tokens
        tokens.append(next_token)

        # Add logit to the list of logits
        logits.append(logit)

    # Concatenate all tokens into a tensor
    tokens = tf.concat(tokens, axis=-1)

    # Convert the translated tokens into text
    translation = tf.squeeze(tokens_to_text(tokens, id_to_word))
    translation = translation.numpy().decode()

    return translation, logits[-1], tokens
```

Try our function with temperature of 0, which will yield a deterministic output and is equivalent to a greedy decoding:

In [ ]:
```
# Running this cell multiple times should return the same output since temp is 0

temp = 0.0
original_sentence = "I love languages"

translation, logit, tokens = translate(trained_translator, original_sentence, temperature=temp)
```

```
print(f"Temperature: {temp}\n\nOriginal sentence: {original_sentence}\nTranslation: {translation}\nTranslation
```

```
Temperature: 0.0

Original sentence: I love languages
Translation: eu adoro idiomas .
Translation tokens:[[  9 522 899   4]]
Logit: -0.266
```

Try our function with temperature of 0.7 (stochastic output):

```
In [ ]: # Running this cell multiple times should return different outputs since temp is not 0
        # You can try different temperatures

        temp = 0.7
        original_sentence = "I love languages"

        translation, logit, tokens = translate(trained_translator, original_sentence, temperature=temp)

        print(f"Temperature: {temp}\n\nOriginal sentence: {original_sentence}\nTranslation: {translation}\nTranslation
```

```
Temperature: 0.7

Original sentence: I love languages
Translation: eu adoro idiomas .
Translation tokens:[[  9 522 899   4]]
Logit: -0.380
```

5. Minimum Bayes-Risk Decoding

Getting the most probable token at each step may not necessarily produce the best results. Another approach is to do Minimum Bayes Risk Decoding or MBR. The general steps to implement this are:

- Take several random samples
- Score each sample against all other samples
- Select the one with the highest score

We will be building helper functions for these steps in the following sections.

With the ability to generate different translations by setting different temperature values and generate a bunch of translations and then determine which one is the best candidate. we will do this by using the provided `generate_samples` function. This function will return any desired number of candidate translations alongside the log-probability for each one:

```
In [ ]: def generate_samples(model, text, n_samples=4, temperature=0.6):

            samples, log_probs = [], []

            # Iterate for n_samples iterations
            for _ in range(n_samples):

                # Save the logit and the translated tensor
                _, logp, sample = translate(model, text, temperature=temperature)

                # Save the translated tensors
                samples.append(np.squeeze(sample.numpy()).tolist())

                # Save the logits
                log_probs.append(logp)

            return samples, log_probs
```

```
In [ ]: samples, log_probs = generate_samples(trained_translator, 'I love languages')

        for s, l in zip(samples, log_probs):
            print(f"Translated tensor: {s} has logit: {l:.3f}")
```

```
Translated tensor: [522, 1026, 4] has logit: -0.210
Translated tensor: [9, 522, 899, 4] has logit: -0.444
Translated tensor: [9, 522, 899, 4] has logit: -0.444
Translated tensor: [9, 522, 899, 4] has logit: -0.444
```

Comparing overlaps

Now that we can generate multiple translations it is time to come up with a method to measure the goodness of each one.One way to achieve this is by comparing each sample against the others.

There are several metrics you can use for this purpose, will be calculating scores for **unigram overlaps**.

One of these metrics is the widely used yet simple Jaccard similarity which gets the intersection over union of two sets. The `jaccard_similarity` function returns this metric for any pair of candidate and reference translations:

In [ ]:
```python
def jaccard_similarity(candidate, reference):

    # Convert the lists to sets to get the unique tokens
    candidate_set = set(candidate)
    reference_set = set(reference)

    # Get the set of tokens common to both candidate and reference
    common_tokens = candidate_set.intersection(reference_set)

    # Get the set of all tokens found in either candidate or reference
    all_tokens = candidate_set.union(reference_set)

    # Compute the percentage of overlap (divide the number of common tokens by the number of all tokens)
    overlap = len(common_tokens) / len(all_tokens)

    return overlap
```

In [ ]:
```python
l1 = [1, 2, 3]
l2 = [1, 2, 3, 4]

js = jaccard_similarity(l1, l2)

print(f"jaccard similarity between lists: {l1} and {l2} is {js:.3f}")
```

```
jaccard similarity between lists: [1, 2, 3] and [1, 2, 3, 4] is 0.750
```

6 - rouge1_similarity

Jaccard similarity is good but a more commonly used metric in machine translation is the ROUGE score. For unigrams, this is called ROUGE-1, we can output the scores for both precision and recall when comparing two samples. To get the final score, we will want to compute the F1-score as given by:

$$score = 2* \frac{(precision * recall)}{(precision + recall)}$$
For the implementation of the `rouge1_similarity` function you want to use the Counter class from the Python standard library:

In [ ]:
```python
def rouge1_similarity(candidate, reference):
    """Computes the ROUGE 1 score between two token lists

    Args:
        candidate (list[int]): Tokenized candidate translation
        reference (list[int]): Tokenized reference translation

    Returns:
        float: Overlap between the two token lists
    """

    # Make a frequency table of the candidate and reference tokens
    candidate_word_counts = Counter(candidate)
    reference_word_counts = Counter(reference)

    # Initialize overlap at 0
    overlap = 0

    # Iterate over the tokens in the candidate frequency table

    for token in candidate_word_counts.keys():

        # Get the count of the current token in the candidate frequency table
        token_count_candidate = candidate_word_counts.get(token,0)

        # Get the count of the current token in the reference frequency table
        token_count_reference = reference_word_counts.get(token,0)

        # Update the overlap by getting the minimum between the two token counts above
        overlap += min(token_count_candidate,token_count_reference)

    # Compute the precision

    precision = overlap/(sum(candidate_word_counts.values()))

    # Compute the recall

    recall = overlap/(sum(reference_word_counts.values()))

    if precision + recall != 0:
        # Compute the Rouge1 Score

        f1_score = 2*(precision*recall)/(precision+recall)

        return f1_score


    return 0 # If precision + recall = 0 then return 0
```

In [ ]:
```python
l1 = [1, 2, 3]
```

```
In [ ]: l1 = [1, 2, 3]
        l2 = [1, 2, 3, 4]

        r1s = rouge1_similarity(l1, l2)

        print(f"rouge 1 similarity between lists: {l1} and {l2} is {r1s:.3f}")
```

```
rouge 1 similarity between lists: [1, 2, 3] and [1, 2, 3, 4] is 0.857
```

Computing the Overall Score

We will now build a function to generate the overall score for a particular sample. We need to compare each sample with all other samples. For instance, if we generated 30 sentences, we will need to compare sentence 1 to sentences 2 through 30. Then, we compare sentence 2 to sentences 1 and 3 through 30, and so forth. At each step, we get the average score of all comparisons to get the overall score for a particular sample. To illustrate, these will be the steps to generate the scores of a 4-sample list.

- Get similarity score between sample 1 and sample 2
- Get similarity score between sample 1 and sample 3
- Get similarity score between sample 1 and sample 4
- Get average score of the first 3 steps. This will be the overall score of sample 1
- Iterate and repeat until samples 1 to 4 have overall scores.

The results will be stored in a dictionary for easy lookups.

7 - average_overlap

```
In [ ]: def average_overlap(samples, similarity_fn):
            """Computes the arithmetic mean of each candidate sentence in the samples

            Args:
                samples (list[list[int]]): Tokenized version of translated sentences
                similarity_fn (Function): Similarity function used to compute the overlap

            Returns:
                dict[int, float]: A dictionary mapping the index of each translation to its score
            """
            # Initialize dictionary
            scores = {}

            # Iterate through all samples (enumerate helps keep track of indexes)
            for index_candidate, candidate in enumerate(samples):


                # Initially overlap is zero
                overlap = 0

                # Iterate through all samples (enumerate helps keep track of indexes)
                for index_sample, sample in enumerate(samples):

                    # Skip if the candidate index is the same as the sample index
                    if index_candidate == index_sample:
                        continue

                    # Get the overlap between candidate and sample using the similarity function
                    sample_overlap = similarity_fn(candidate, sample)

                    # Add the sample overlap to the total overlap
                    overlap += sample_overlap


                # Get the score for the candidate by computing the average
                score = overlap / (len(samples) - 1)

                # Only use 3 decimal points
                score = round(score, 3)

                # Save the score in the dictionary. use index as the key.
                scores[index_candidate] = score

            return scores
```

```
In [ ]: # Test with Jaccard similarity

        l1 = [1, 2, 3]
        l2 = [1, 2, 4]
        l3 = [1, 2, 4, 5]

        avg_ovlp = average_overlap([l1, l2, l3], jaccard_similarity)

        print(f"average overlap between lists: {l1}, {l2} and {l3} using Jaccard similarity is:\n\n{avg_ovlp}")
```

```
average overlap between lists: [1, 2, 3], [1, 2, 4] and [1, 2, 4, 5] using Jaccard similarity is:

{0: 0.45, 1: 0.625, 2: 0.575}
```

In [ ]:
```
# Test with Rouge1 similarity

l1 = [1, 2, 3]
l2 = [1, 4]
l3 = [1, 2, 4, 5]
l4 = [5,6]

avg_ovlp = average_overlap([l1, l2, l3, l4], rouge1_similarity)

print(f"average overlap between lists: {l1}, {l2}, {l3} and {l4} using Rouge1 similarity is:\n\n{avg_ovlp}")
```

```
average overlap between lists: [1, 2, 3], [1, 4], [1, 2, 4, 5] and [5, 6] using Rouge1 similarity is:

{0: 0.324, 1: 0.356, 2: 0.524, 3: 0.111}
```

In practice, it is also common to see the weighted mean being used to calculate the overall score instead of just the arithmetic mean. This is implemented in the `weighted_avg_overlap` function below and you can use it in your experiments to see which one will give better results:

In [ ]:
```
def weighted_avg_overlap(samples, log_probs, similarity_fn):

    # Scores dictionary
    scores = {}

    # Iterate over the samples
    for index_candidate, candidate in enumerate(samples):

        # Initialize overlap and weighted sum
        overlap, weight_sum = 0.0, 0.0

        # Iterate over all samples and log probabilities
        for index_sample, (sample, logp) in enumerate(zip(samples, log_probs)):

            # Skip if the candidate index is the same as the sample index
            if index_candidate == index_sample:
                continue

            # Convert log probability to linear scale
            sample_p = float(np.exp(logp))

            # Update the weighted sum
            weight_sum += sample_p

            # Get the unigram overlap between candidate and sample
            sample_overlap = similarity_fn(candidate, sample)

            # Update the overlap
            overlap += sample_p * sample_overlap

        # Compute the score for the candidate
        score = overlap / weight_sum

        # Only use 3 decimal points
        score = round(score, 3)

        # Save the score in the dictionary. use index as the key.
        scores[index_candidate] = score

    return scores
```

In [ ]:
```
l1 = [1, 2, 3]
l2 = [1, 2, 4]
l3 = [1, 2, 4, 5]
log_probs = [0.4, 0.2, 0.5]

w_avg_ovlp = weighted_avg_overlap([l1, l2, l3], log_probs, jaccard_similarity)

print(f"weighted average overlap using Jaccard similarity is:\n\n{w_avg_ovlp}")
```

```
weighted average overlap using Jaccard similarity is:

{0: 0.443, 1: 0.631, 2: 0.558}
```

mbr_decode

We will now put everything together in the the `mbr_decode` function below. This final st is just a wrapper around all the cool stuff we have coded so far!

we can use it to play around, trying different numbers of samples, temperatures and similarity functions!

In [ ]:
```
def mbr_decode(model, text, n_samples=5, temperature=0.6, similarity_fn=jaccard_similarity):
    # Generate samples
    samples, log_probs = generate_samples(model, text, n_samples=n_samples, temperature=temperature)

    # Compute the overlap scores
    scores = weighted_avg_overlap(samples, log_probs, similarity_fn)

    # Decode samples
    decoded_translations = [tokens_to_text(s, id_to_word).numpy().decode('utf-8') for s in samples]

    # Find the key with the highest score
    max_score_key = max(scores, key=lambda k: scores[k])

    # Get the translation
    translation = decoded_translations[max_score_key]

    return translation, decoded_translations
```

Try Your Own Sentence !

In [ ]:

```
english_sentence = "I love languages"

translation, candidates = mbr_decode(trained_translator, english_sentence, n_samples=10, temperature=0.6)

print("Translation candidates:")
for c in candidates:
    print(c)

print(f"\nSelected translation: {translation}")
```

```
Translation candidates:
eu adoro idiomas .
eu adoro linguas .
eu adoro idiomas .
eu adoro linguas .
eu adoro idiomas .
eu adoro idiomas .
eu adoro linguas .
eu adoro idiomas .
eu adoro idiomas .
adoro linguas .

Selected translation: eu adoro idiomas .
```