

RNN_Lab

May 6, 2025

1 RNN Machine Translation Laboration

In this lab, your task is to build a sequence-to-sequence model, using recurrent neural networks, that translates short sentences from Swedish into English.

```
[1]: import os
os.environ["TF_CPP_MIN_LOG_LEVEL"] = "2" # Tensorflow is quite chatty; filter_
↳ out warnings
```

```
[2]: import tensorflow as tf
import tf_keras as keras
from tf_keras import layers
```

```
2025-05-06 13:32:52.333036: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1746531172.366048 668362 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1746531172.376626 668362 cuda_blas.cc:1418] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
```

1.0.1 Check that Tensorflow uses a GPU (*optional*)

Training the models in this notebook can be sped up significantly with a GPU. The following cell can be used to check if the GPU is set up correctly. If you run on CPU, you can either run or just ignore this cell.

```
[3]: os.environ["CUDA_DEVICE_ORDER"]="PCI_BUS_ID"
# The GPU id to use, usually either "0" or "1"
os.environ["CUDA_VISIBLE_DEVICES"]="0"

if tf.config.list_physical_devices("GPU"):
    print(" Tensorflow has detected a GPU.")
    import shutil
```

```

if not shutil.which("ptxas"):
    print("\n Command 'ptxas' not found in path -- you might have to
↪install `cudatoolkit-dev`")
if not "XLA_FLAGS" in os.environ:
    print("\n XLA_FLAGS not set. If you encounter errors during training,
↪you might have to set")
    print("          XLA_FLAGS=\"--xla_gpu_cuda_data_dir=$CONDA_PREFIX/lib/
↪\"")

    # Allow growth of GPU memory, otherwise it will always look like all the
↪memory is being used
    physical_devices = tf.config.experimental.list_physical_devices('GPU')
    tf.config.experimental.set_memory_growth(physical_devices[0], True)
else:
    print(" Tensorflow has NOT detected a GPU.")
    print()
    print("For GPU support, visit: <https://www.tensorflow.org/install/pip>")

```

Tensorflow has detected a GPU.

XLA_FLAGS not set. If you encounter errors during training, you might have to set

```
XLA_FLAGS="--xla_gpu_cuda_data_dir=$CONDA_PREFIX/lib/"
```

1.1 Problem Specification

Your task in this assignment is to:

1. Build an encoder—decoder model based on recurrent neural networks.
2. Train this model on the provided training data, a collection of parallel Swedish–English sentences.
3. Evaluate the performance of this model on the provided test data.

1.1.1 The data: Swedish–English Anki corpus

The data in this lab consists of bilingual Swedish–English sentence pairs from the [Tatoeba Project](#) as collected by [Anki](#). These are comparatively short sentences, suitable for language learners, and therefore also well-suited for building a small machine translation model. Here are some example sentences from the training set:

```

[4]: with open("en-sv-train.txt", "rt", encoding="utf-8") as f:
    for i, line in enumerate(f):
        pair = [sent for sent in line.rstrip().split("\t")]
        print(pair)
        if i > 2:
            break

```

```

['i returned to japan .', 'jag återvände till japan .']
['i love her .', 'jag älskar henne .']

```

```
["this is tom ' s school .", 'detta är toms skola .']  
['i can hardly stand .', 'jag kan knappt stå .']
```

Each line in the data files consists of an English–Swedish sentence pair. The sentences are already lower-cased and pre-tokenized (using the [toktok tokenizer from NLTK](#)), so we can simply split them up by whitespace to get sequences of tokens. To make your life a bit easier, we have removed sentences longer than 15 words.

The next cell contains code that yields the sentences contained in a file as lists of strings:

```
[5]: ENGLISH = 0  
      SWEDISH = 1  
  
      def sentences(filename, idx):  
          # Use idx=0 for English, idx=1 for Swedish  
          with open(filename, "rt", encoding="utf-8") as source:  
              for line in source:  
                  yield line.rstrip().split("\t")[idx].split()  
  
      # Example usage  
      next(sentences("en-sv-train.txt", ENGLISH))
```

```
[5]: ['i', 'returned', 'to', 'japan', '.']
```

1.2 Part 1: Build the vocabularies

Before we can feed them into any model, we first need to convert the text strings to integers. For this purpose, we’ll create a **vocabulary** of tokens that are known to the model, one vocabulary for each language. We need four **special tokens** (or “pseudowords”):

1. <pad> at index 0 for padding purposes
2. <unk> at index 1 to represent unknown words
3. <bos> at index 2 to mark the “beginning of sequence” in the decoder
4. <eos> at index 3 to mark the “end of sequence” in the decoder

The remaining items in the vocabulary should be made up of the **most frequent words** in the training data for the respective language.

Task 1: Write the function to build the vocabularies

```
[6]: from collections import Counter  
  
      def make_vocab(sentences, max_size):  
          """Return a list of the `max_size` most frequent tokens in `sentences`."""  
  
          # TODO  
          # 1. Count of how often each word occurs in the data  
          # 2. Sort the words by their frequency, in descending order  
          # 3. Make a list of the special tokens plus the most frequent words, up to  
          ↪ a length of `max_size`.
```

```

# 4. Return the list

if isinstance(sentences, str):
    sentences = [sentences.split()]
words = []
for sentence in sentences:
    for word in sentence:
        words.append(word)
word_counts = Counter(words)
sorted_words = []
for word, count in word_counts.most_common():
    sorted_words.append(word)

added_words = ['<pad>', '<unk>', '<bos>', '<eos>']

count = max_size - len(added_words)

final_words = added_words + sorted_words[:count]

return final_words

```

With this function, we can construct vocabularies containing the 5,000 most frequent words as follows:

```

[7]: src_vocab = make_vocab(sentences('en-sv-train.txt', SWEDISH), 5000)
     tgt_vocab = make_vocab(sentences('en-sv-train.txt', ENGLISH), 5000)

```

Test your code To test your code, check that each vocabulary contains 5,000 words, and includes the pseudowords at the right positions:

```

[8]: def test1():
     assert len(src_vocab) == 5000
     assert len(tgt_vocab) == 5000
     assert src_vocab[:4] == ['<pad>', '<unk>', '<bos>', '<eos>']
     assert tgt_vocab[:4] == ['<pad>', '<unk>', '<bos>', '<eos>']
     print("All good!")

test1()

```

All good!

1.2.1 Wrap the vocabularies in StringLookup layers

For mapping tokens to their vocabulary IDs, we can use Keras' `StringLookup` layer. The next cell constructs layers for both the source and target vocabulary.

```

[9]:

```

```
string_lookup_args = dict(output_mode="int", mask_token="<pad>",
    ↪oov_token="<unk>")
src_lookup = layers.StringLookup(vocabulary=src_vocab, **string_lookup_args)
tgt_lookup = layers.StringLookup(vocabulary=tgt_vocab, **string_lookup_args)
```

```
I0000 00:00:1746531269.883318 668362 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 17983 MB memory: -> device:
0, name: NVIDIA RTX 4000 Ada Generation, pci bus id: 0000:01:00.0, compute
capability: 8.9
```

The next cell gives an example how these `StringLookup` layers can be used. Note that the layers already return *tensors*.

```
[10]: example = "i returned to japan yesterday ".split()
      print(tgt_lookup(example))
```

```
tf.Tensor([ 5 1005 11 530 188 4], shape=(6,), dtype=int64)
```

Task 2: Sanity-check that these numbers are correct Check your understanding of what’s happening in the `StringLookup` layer by writing two lines of code: 1. One that prints the token corresponding to the *second integer* in the tensor above. 2. One that prints the integer corresponding to the *second word* (“returned”) in the example above.

Use `tgt_vocab` directly for that, not the lookup layer!

```
[11]: #print(tgt_vocab[1])
      #word_index = tgt_vocab.index("returned")
      #if(word_index.is_integer):
      #    print(word_index)
      #else:
      #    print("Word not found")
      print(tgt_vocab[1])
      word_index = tgt_vocab.index("returned")
      if(isinstance(word_index, int)):
          print(word_index)
      else:
          print("Word not found")
```

```
<unk>
1005
```

1.2.2 Wrapping everything in data loaders

The next cell defines a function that wraps our dataset in TensorFlow’s `tf.data.Dataset` API, which represents map-style datasets. The advantage of this is that it lets us use standard infrastructure related to the loading and automatic batching of data.

```
[12]: def append_eos(tensor):
      "Helper function that appends '<eos>' to a sequence."
```

```

    return tf.concat([tensor, tf.constant(["<eos>"], dtype=tf.string)], axis=0)

def load_translation_dataset(src_lookup, tgt_lookup, filename):
    # Build source dataset and convert with src_lookup
    src_dataset = tf.data.Dataset.from_tensor_slices(
        tf.ragged.constant(list(sentences(filename, SWEDISH)))
    )
    src_dataset = src_dataset.map(src_lookup)

    # Build target dataset, append <eos> and convert with tgt_lookup
    tgt_dataset = tf.data.Dataset.from_tensor_slices(
        tf.ragged.constant(list(sentences(filename, ENGLISH)))
    )
    tgt_dataset = tgt_dataset.map(append_eos).map(tgt_lookup)

    # Zip them together
    return tf.data.Dataset.zip((src_dataset, tgt_dataset))

```

We load the training data:

```

[13]: train_dataset = load_translation_dataset(src_lookup, tgt_lookup, "en-sv-train.
      ↪txt")

```

The following function can be helpful for debugging. It extracts a single source–target pair of sentences from the specified *dataset* and converts it into batches of size 1, which can be fed into the encoder–decoder model. This also illustrates how the `Dataset` API works:

```

[14]: def example(dataset, i):
      if i > 0:
          dataset = dataset.skip(i-1)
      return list(dataset.take(1).batch(1))[0]

```

```

[15]: x, y = example(train_dataset, 42)
      print(x)
      print(y)

```

```

tf.Tensor([[ 6  10 245  15  20   7]], shape=(1, 6), dtype=int64)
tf.Tensor([[ 29   9 477  55  28   8   3]], shape=(1, 7), dtype=int64)

```

1.3 Part 2: The encoder–decoder architecture

In this section, you will implement the encoder–decoder architecture, including the extension of that architecture by an attention mechanism. The implementation consists of four parts: the encoder, the attention mechanism, the decoder, and a class that wraps the complete architecture.

1.3.1 Part 2.1: Implement the encoder

The encoder is a component that takes an input tensor of vocabulary IDs, like the `x` tensor from the example above, and performs the following steps:

1. Look up **word embeddings** for each token in the sequence.
2. Process them with a **bi-directional recurrent neural network**. This works with any type of RNN, but we will use **GRU (gated recurrent unit) layers** throughout this laboration.
3. Feed the output through a linear layer. We also take the last hidden state of the forward GRU and the last hidden state of the backward GRU, concatenate them, and pass them through a linear layer. This produces a “summary” of the source sentence, which we will later feed into the decoder.

Let's implement the encoder by defining it as a **custom Keras layer**. For this, we have to define a class that subclasses from `keras.layers.Layer`, instantiate all required model weights and/or (sub)layers in the `__init__()` function, and uses them to perform the layer's computation in the `call()` function. Below is some skeleton code to get you started; you can also [read more about making custom layers in the Keras Docs](#).

Task 3: Implement the encoder by completing the skeleton code below

```
[16]: # class Encoder(layers.Layer):
#     def __init__(self, num_words, embedding_dim=128, hidden_dim=256):
#         super().__init__()
#         # TODO: Add your code here that defines the required layers/weights
#         self.embedding = ...
#         self.rnn = ...
#         self.linear = ...

#     def call(self, inputs):
#         # TODO
#         # 1. Look up the embeddings for the source words
#         # 2. Apply a bi-directional GRU over the source sequences
#         # 3. Apply a linear transformation to the GRU's output
#         # 4. Concatenate forward + backward hidden states and apply a linear
#         ↪ transformation on them too
#         raise NotImplementedError

class Encoder(layers.Layer):
    def __init__(self, num_words, embedding_dim=128, hidden_dim=256):
        super().__init__()
        # TODO: Add your code here that defines the required layers/weights
        self.embedding = layers.Embedding(input_dim=num_words,
        ↪ output_dim=embedding_dim, mask_zero=True)
        self.rnn = layers.Bidirectional(layers.GRU(hidden_dim,
        ↪ return_sequences=True, return_state=True))
        self.linear = layers.Dense(hidden_dim)

    def call(self, inputs):
        # TODO
        # 1. Look up the embeddings for the source words
        embeddings = self.embedding(inputs)
        # 2. Apply a bi-directional GRU over the source sequences
        results = self.rnn(embeddings)
```

```

        output = results[0]
        forward = results[1]
        backward = results[2]
        # 3. Apply a linear transformation to the GRU's output
        linear_transformed = self.linear(output)
        # 4. Concatenate forward + backward hidden states and apply a linear
        ↪ transformation on them too
        state = tf.concat([forward, backward], axis=-1)
        summary = self.linear(state)
        return linear_transformed, summary

```

Your code must comply with the following specification:

init (*num_words*, *embedding_dim* = 128, *hidden_dim* = 256)

Initialises the encoder. The encoder consists of an embedding layer that maps each of *num_words* words to an embedding vector of size *embedding_dim*, a bidirectional GRU that maps each embedding vector to a position-specific representation of size $2 \times \textit{hidden_dim}$, and a final linear layer that projects these representations to new representations of size *hidden_dim*.

call (*self*, *inputs*)

Takes a tensor *inputs* with source-language word ids and sends it through the encoder. The input tensor has shape (*batch_size*, *src_len*), where *src_len* is the length of the sentences in the batch. (We will make sure that all sentences in the same batch have the same length.) The method returns a pair of tensors (*output*, *hidden*), where *output* has shape (*batch_size*, *src_len*, *hidden_dim*), and *hidden* has shape (*batch_size*, *hidden_dim*).

Test your code To test your code, instantiate an encoder, feed it the first source sentence in the training data, and check that the tensors returned by the encoder have the expected shapes.

```

[17]: def test21():
        src, tgt = example(train_dataset, 42)
        encoder = Encoder(src_lookup.vocabulary_size())
        output, hidden = encoder(src)
        print(output.shape) # should be (batch_size, src_len, hidden_dim)
        print(hidden.shape) # should be (batch_size, hidden_dim)

test21()

```

```
(1, 6, 256)
```

```
(1, 256)
```

```
I0000 00:00:1746531562.638179 672657 cuda_dnn.cc:529] Loaded cuDNN version
90300
```


1.3.2 Part 2.2: Implement the attention mechanism

Your next task is to implement the attention mechanism. Recall that the purpose of this mechanism is to inform the decoder when generating the translation of the next word. For this, attention has access to the previous hidden state of the decoder, as well as the complete output of the encoder. It returns the attention-weighted sum of the encoder output, the so-called *context* vector. For later usage, we also return the attention weights.

As mentioned in the lecture, attention can be implemented in various ways. One very simple implementation is *uniform attention*, which assigns equal weight to each position-specific representation in the output of the encoder, and completely ignores the hidden state of the decoder. This mechanism is implemented in the cell below:

```
[18]: class UniformAttention(layers.Layer):
    def __init__(self):
        super().__init__()
        self.supports_masking = True

    def call(self, decoder_hidden, encoder_output, mask=None):
        # Set all attention scores to the same constant value (0). After
        # the softmax, we will have uniform weights.
        scores = tf.zeros_like(encoder_output[:, :, -1])

        # Mask out the attention scores for the padding tokens. We set
        # them to -inf. After the softmax, we will have 0.
        if mask is not None:
            masked_value = -float('inf') * tf.ones_like(scores)
            scores = tf.where(mask, scores, masked_value)

        # Convert scores into weights
        alpha = tf.nn.softmax(scores, axis=1)

        # The context is the alpha-weighted sum of the encoder outputs.
        context = tf.linalg.matmul(tf.expand_dims(alpha, axis=1),
        ↪ encoder_output)
        context = tf.squeeze(context, axis=1)

    return alpha, context
```

One technical detail in this code is our use of *mask* to compute attention weights only for the ‘real’ tokens in the source sentences, but not for the padding tokens that we introduce to bring all sentences in a batch to the same length.

Your task now is to implement the attention mechanism from the paper by [Bahdanau et al. \(2015\)](#). The relevant equation is in Section A.1.2:

$$a(s_{i-1}, h_j) = v^\top \tanh(Ws_{i-1} + Uh_j)$$

This equation specifies how to compute the attention score (a scalar) for the previous hidden state

of the decoder, denoted by s_{i-1} , and the j -th position-specific representation in the output of the encoder, denoted by h_j . The equation refers to three parameters: a vector v and W and U . In PyTorch, these parameters can be represented in terms of (bias-free) linear layers that are trained along with the other parameters of the model.

Here is the skeleton code for this problem. As you can see, your specific task is to initialise the required parameters and to compute the attention scores (*scores*); the rest of the code is the same as for the uniform attention.

Task 4: Implement Bahdanau attention by completing the skeleton code below

```
[19]: # class BahdanauAttention(layers.Layer):
#     def __init__(self, hidden_dim=256):
#         super().__init__()
#         self.supports_masking = True
#         # TODO: Add your code here that defines the required layers/weights
#         self.w = ...
#         self.u = ...
#         self.v = ...

#     def call(self, decoder_hidden, encoder_output, mask=None):
#         # TODO: Replace the next line with your own code that computes the
#         ↪ attention scores
#         scores = tf.zeros_like(encoder_output[:, :, -1])

#         # ... The rest of the code is as in UniformAttention - NO NEED TO
#         ↪ MODIFY BELOW THIS LINE!

#         # Mask out the attention scores for the padding tokens. We set
#         # them to -inf. After the softmax, we will have 0.
#         if mask is not None:
#             masked_value = -float('inf') * tf.ones_like(scores)
#             scores = tf.where(mask, scores, masked_value)

#         # Convert scores into weights
#         alpha = tf.nn.softmax(scores, axis=1)

#         # The context is the alpha-weighted sum of the encoder outputs.
#         context = tf.linalg.matmul(tf.expand_dims(alpha, axis=1),
#         ↪ encoder_output)
#         context = tf.squeeze(context, axis=1)

#         return alpha, context
class BahdanauAttention(layers.Layer):
    def __init__(self, hidden_dim=256):
        super().__init__()
        self.supports_masking = True
        # TODO: Add your code here that defines the required layers/weights
```

```

self.w = layers.Dense(hidden_dim, use_bias=False) # For encoder outputs
self.u = layers.Dense(hidden_dim, use_bias=False)
self.v = layers.Dense(1, use_bias=False)

def call(self, decoder_hidden, encoder_output, mask=None):
    # TODO: Replace the next line with your own code that computes the
    ↪ attention scores
    hidden_decoder = tf.expand_dims(decoder_hidden, axis=1)
    encoder = self.w(encoder_output)
    decoder = self.u(hidden_decoder)
    res = tf.nn.tanh(encoder + decoder)
    scores = tf.squeeze(self.v(res), axis=-1)

    # ... The rest of the code is as in UniformAttention - NO NEED TO
    ↪ MODIFY BELOW THIS LINE!

    # Mask out the attention scores for the padding tokens. We set
    # them to -inf. After the softmax, we will have 0.
    if mask is not None:
        masked_value = -float('inf') * tf.ones_like(scores)
        scores = tf.where(mask, scores, masked_value)

    # Convert scores into weights
    alpha = tf.nn.softmax(scores, axis=1)

    # The context is the alpha-weighted sum of the encoder outputs.
    context = tf.linalg.matmul(tf.expand_dims(alpha, axis=1),
    ↪ encoder_output)
    context = tf.squeeze(context, axis=1)

    return alpha, context

```

Your code must comply with the following specification:

call (*decoder_hidden*, *encoder_output*, *mask*)

Takes the previous hidden state of the decoder (*decoder_hidden*) and the encoder output (*encoder_output*) and returns a pair (*alpha*, *context*) where *context* is the context as computed as in [Bahdanau et al. \(2015\)](#), and *alpha* are the corresponding attention weights. The hidden state has shape (*batch_size*, *hidden_dim*), the encoder output has shape (*batch_size*, *src_len*, *hidden_dim*), the context has shape (*batch_size*, *hidden_dim*), and the attention weights have shape (*batch_size*, *src_len*).

Hints on the implementation You may need a few more “low-level” TensorFlow functions to implement this part, concretely:

- `tf.expand_dims()` and `tf.squeeze()` to add/remove a dimension from a tensor. This is because some tensors have a “timestep” dimension while others (e.g. the hidden state of the decoder) don’t.

- `tf.nn.tanh()` to compute the tanh function on a tensor.

Test your code To test your code, extend your test from Task 3: Feed the output of your encoder into your attention class. As the previous hidden state of the decoder, you can use the hidden state returned by the encoder. Later, you don't need to pass the mask explicitly (Keras will do this automatically), but for testing purposes, you can obtain the mask from a layer's output via `output._keras_mask`.

Check that the context tensor and the attention weights returned by the attention class have the expected shapes.

```
[20]: def test22():
    src, tgt = example(train_dataset, 42)
    encoder = Encoder(src_lookup.vocabulary_size())
    output, hidden = encoder(src)
    attention = BahdanauAttention()
    alpha, context = attention(hidden, output, mask=output._keras_mask)
    print(alpha.shape)      # should be (batch_size, src_len)
    print(context.shape)    # should be (batch_size, hidden_dim)

test22()
```

```
(1, 6)
(1, 256)
```

1.3.3 Part 2.3: Implement the decoder

Now you are ready to implement the decoder. Like the encoder, the decoder is based on a GRU; but this time we use a unidirectional network, as we generate the target sentences left-to-right.

We expect that solving this problem will take you the longest time in this lab.

Because the decoder is an autoregressive model, we need to unroll the GRU “manually”: At each position, we take the previous hidden state as well as the new input, and apply the GRU for one step. The initial hidden state comes from the encoder. The new input is the embedding of the previous word, concatenated with the context vector from the attention model. To produce the final output, we take the output of the GRU, concatenate the embedding vector and the context vector (residual connection), and feed the result into a linear layer. Here is a graphical representation:

We need to implement this manual unrolling for two very similar tasks: When *training*, both the inputs to and the target outputs of the GRU come from the training data. When *decoding*, the outputs of the GRU are used to generate new target-side words, and these words become the inputs to the next step of the unrolling. **We have already implemented the call method that handles both these two different modes of usage — you don't need to modify this.**

Task 5: Implement the `step` method that takes a single step with the GRU You will also need to add any necessary layers/weights that you use in the `__init__` function.

```
[21]:
```

```

# class Decoder(layers.Layer):
#     def __init__(self, trg_lookup, attention, embedding_dim=128,
# ↪hidden_dim=256, max_len=16):
#         super().__init__()
#         num_words = trg_lookup.vocabulary_size()
#         self.embedding = layers.Embedding(num_words, embedding_dim,
# ↪mask_zero=True)
#         self.bos_index = trg_lookup(["<bos>"]).numpy()
#         self.max_len = max_len
#         # TODO: Add your code here that defines the required layers/weights
#         self.attention = ...
#         self.rnn_cell = ...
#         self.linear = ...

#     def call(self, encoder_output, initial_state, targets=None,
# ↪training=False, mask=None):
#         # YOU WON'T NEED TO MODIFY ANYTHING IN THIS FUNCTION.

#         if training:
#             assert targets is not None

#         # Initialise the hidden state from `initial_state`
#         state = initial_state

#         # Initialise the decoder input with the `<bos>` symbol
#         next_input = self.bos_index * tf.ones_like(initial_state, dtype=tf.
# ↪int64)
#         next_input = next_input[:, 0]

#         # Initialise the list of outputs and attention weights
#         outputs = tf.TensorArray(
#             tf.float32,
#             size=0 if training else self.max_len,
#             dynamic_size=training,
#         )
#         alphas = tf.TensorArray(
#             tf.float32,
#             size=0 if training else self.max_len,
#             dynamic_size=training,
#         )
#         inputs = tf.TensorArray(
#             tf.int64,
#             size=0 if training else self.max_len,
#             dynamic_size=training,
#         )

```

```

#         # In training mode, we iterate over the length of the target
#         ↪ sentences,
#         # otherwise we iterate until `self.max_len` is reached
#         max_len = tf.shape(targets)[1] if training else self.max_len

#         for i in range(max_len):
#             # In training mode, we feed the correct (gold) predictions as the
#             ↪ next input
#             if training and i > 0:
#                 next_input = targets[:, i-1]

#             # Get the embedding for the previous word
#             prev_embed = self.embedding(next_input)

#             # Take one step with the RNN
#             step_output, state, alpha = self.step(encoder_output, state,
#             ↪ prev_embed, mask=mask)

#             # Update the list of generated words and attention weights
#             outputs = outputs.write(i, step_output)
#             alphas = alphas.write(i, alpha)
#             inputs = inputs.write(i, next_input)

#             # Set the prediction with highest probability as the input for
#             ↪ the next timestep
#             if not training:
#                 next_input = tf.math.argmax(step_output, axis=-1)

#             # Lists of outputs and attention weights are [tgt_len, batch_size, *],
#             # so we transpose them to have the batch dimension in first place
#             ↪ again.
#             outputs = tf.transpose(outputs.stack(), perm=[1,0,2])
#             alphas = tf.transpose(alphas.stack(), perm=[1,0,2])
#             inputs = tf.transpose(inputs.stack(), perm=[1,0])
#             outputs._keras_mask = (inputs != 0)

#             return outputs, alphas

#     def step(self, encoder_output, hidden_state, prev_embed, mask=None):
#         # TODO: Replace the next line with your own code; this should follow
#         ↪ the illustration above.
#         # 1. Get the attention weights and context vector
#         alpha, context = ...
#         # 2. Concatenate the inputs for the GRU
#         rnn_input = ...
#         # 3. Take one step with the GRU cell

```

```

#         rnn_output, hidden_state = ...
#         # 4. Concatenate the respective tensors to produce the final output
#         output = ...

#         return output, hidden_state, alpha
class Decoder(layers.Layer):
    def __init__(self, trg_lookup, attention, embedding_dim=128,
        ↪hidden_dim=256, max_len=16):
        super().__init__()
        num_words = trg_lookup.vocabulary_size()
        self.embedding = layers.Embedding(num_words, embedding_dim,
        ↪mask_zero=True)
        self.bos_index = trg_lookup(["<bos>"]).numpy()
        self.max_len = max_len
        # TODO: Add your code here that defines the required layers/weights
        self.attention = attention
        self.rnn_cell = layers.GRUCell(hidden_dim)
        self.linear = layers.Dense(num_words)

    def call(self, encoder_output, initial_state, targets=None, training=False,
        ↪mask=None):
        # YOU WON'T NEED TO MODIFY ANYTHING IN THIS FUNCTION.

        if training:
            assert targets is not None

        # Initialise the hidden state from `initial_state`
        state = initial_state

        # Initialise the decoder input with the `<bos>` symbol
        next_input = self.bos_index * tf.ones_like(initial_state, dtype=tf.
        ↪int64)
        next_input = next_input[:, 0]

        # Initialise the list of outputs and attention weights
        outputs = tf.TensorArray(
            tf.float32,
            size=0 if training else self.max_len,
            dynamic_size=training,
        )
        alphas = tf.TensorArray(
            tf.float32,
            size=0 if training else self.max_len,
            dynamic_size=training,
        )
        inputs = tf.TensorArray(
            tf.int64,

```

```

        size=0 if training else self.max_len,
        dynamic_size=training,
    )

    # In training mode, we iterate over the length of the target sentences,
    # otherwise we iterate until `self.max_len` is reached
    max_len = tf.shape(targets)[1] if training else self.max_len

    for i in range(max_len):
        # In training mode, we feed the correct (gold) predictions as the
        ↪next input
        if training and i > 0:
            next_input = targets[:, i-1]

        # Get the embedding for the previous word
        prev_embed = self.embedding(next_input)

        # Take one step with the RNN
        step_output, state, alpha = self.step(encoder_output, state,
        ↪prev_embed, mask=mask)

        # Update the list of generated words and attention weights
        outputs = outputs.write(i, step_output)
        alphas = alphas.write(i, alpha)
        inputs = inputs.write(i, next_input)

        # Set the prediction with highest probability as the input for the
        ↪next timestep
        if not training:
            next_input = tf.math.argmax(step_output, axis=-1)

    # Lists of outputs and attention weights are [tgt_len, batch_size, *],
    # so we transpose them to have the batch dimension in first place again.
    outputs = tf.transpose(outputs.stack(), perm=[1,0,2])
    alphas = tf.transpose(alphas.stack(), perm=[1,0,2])
    inputs = tf.transpose(inputs.stack(), perm=[1,0])
    outputs._keras_mask = (inputs != 0)

    return outputs, alphas

def step(self, encoder_output, hidden_state, prev_embed, mask=None):
    # TODO: Replace the next line with your own code; this should follow
    ↪the illustration above.
    # 1. Get the attention weights and context vector
    alpha, context = self.attention(hidden_state, encoder_output,
    ↪mask=encoder_output._keras_mask)
    # 2. Concatenate the inputs for the GRU

```



```

rnn_input = tf.concat([prev_embed, context], axis=-1)
# 3. Take one step with the GRU cell
rnn_output, hidden_state = self.rnn_cell(rnn_input, hidden_state)
# 4. Concatenate the respective tensors to produce the final output
output = self.linear(tf.concat([rnn_output, rnn_input], axis=-1))

return output, hidden_state, alpha

```

Your implementation should comply with the following specification:

step (*self*, *encoder_output*, *hidden*, *prev_embed*, *mask*)

Performs a single step in the manual unrolling of the decoder GRU. This takes the output of the encoder (*encoder_output*), the previous hidden state of the decoder (*hidden*), the embedding vector of the previous word (*prev_embed*), and the source mask as described in Problem 2.2 (*mask*), and computes the output as described above.

The shape of *encoder_output* is (*batch_size*, *src_len*, *hidden_dim*); the shape of *hidden* is (*batch_size*, *hidden_dim*); the shape of *src_mask* is (*batch_size*, *src_len*); and the shape of *prev_embed* is (*batch_size*, *embedding_dim*).

The method returns a triple of tensors (*output*, *hidden*, *alpha*) where *output* is the position-specific output of the GRU, of shape (*batch_size*, *num_words*); *hidden* is the new hidden state, of shape (*batch_size*, *hidden_dim*); and *alpha* are the attention weights that were used to compute the *output*, of shape (*batch_size*, *src_len*).

Hints on the implementation GRU vs. GRUCell. In Keras, an RNN layer like GRU is used to process an entire sequence. A single *time-step* of a sequence is handled by a [GRUCell](#) instead. You can think of a GRU layer as functionally equivalent to a for-loop around a [GRUCell](#). Since we want to perform the RNN steps individually for this model, you should use a [GRUCell](#) instead of a GRU layer here.

Test your code To test your code, extend your test from the previous problems, and simulate a complete forward pass of the encoder-decoder architecture on the example sentence. Check the shapes of the resulting tensors.

```

[22]: def test23():
    src, tgt = list(train_dataset.take(4).padded_batch(4))[0]
    encoder = Encoder(src_lookup.vocabulary_size())
    encoder_output, hidden = encoder(src)
    attention = BahdanauAttention()
    decoder = Decoder(tgt_lookup, attention)
    decoded, alphas = decoder(encoder_output, hidden)
    print(decoded.shape) # should be (batch_size, max_len, vocabulary_size)
    print(alphas.shape) # should be (batch_size, max_len, src_len)
    decoded, _ = decoder(encoder_output, hidden, targets=tgt, training=True)
    print(decoded.shape) # should be (batch_size, tgt_len, vocabulary_size)

test23()

```

```
(4, 16, 5000)
(4, 16, 5)
(4, 8, 5000)
```

1.3.4 Encoder–Decoder wrapper class

The last part of the implementation is a class that wraps the encoder and the decoder as a single model. We also implement a custom `train_step` function so that the gold targets will get passed to the decoder during training, and a custom `test_step` function to make sure the decoded sequences and the gold sequences are padded to the same length before computing losses and evaluation metrics.

```
[23]: class EncoderDecoder(keras.Model):
    def __init__(self, src_lookup, tgt_lookup, embedding_dim=128,
        hidden_dim=256, max_len=16, **kwargs):
        super().__init__(**kwargs)
        self.encoder = Encoder(
            src_lookup.vocabulary_size(),
            embedding_dim=embedding_dim,
            hidden_dim=hidden_dim
        )
        self.decoder = Decoder(
            tgt_lookup,
            BahdanauAttention(hidden_dim=hidden_dim),
            embedding_dim=embedding_dim,
            hidden_dim=hidden_dim,
            max_len=max_len,
        )

    def call(self, inputs, training=False, targets=None):
        x_out, x_hidden = self.encoder(inputs, training=training)
        outputs, alphas = self.decoder(x_out, x_hidden, training=training,
            targets=targets)
        if training:
            return outputs
        else:
            return outputs, alphas

    # Following <https://keras.io/guides/customizing_what_happens_in_fit/>
    def train_step(self, data):
        x, y = data

        with tf.GradientTape() as tape:
            # Here we supply "targets" so that the decoder has access to it
            y_pred = self(x, training=True, targets=y)
            loss = self.compiled_loss(y, y_pred, regularization_losses=self.
                losses)
```

```

trainable_vars = self.trainable_variables
gradients = tape.gradient(loss, trainable_vars)
self.optimizer.apply_gradients(zip(gradients, trainable_vars))
self.compiled_metrics.update_state(y, y_pred)
return {m.name: m.result() for m in self.metrics}

def test_step(self, data):
    x, y = data
    y_pred, _alphas = self(x, training=False)

    # Pad sequences to the same number of time-steps
    max_len = tf.math.maximum(tf.shape(y)[1], tf.shape(y_pred)[1])
    y_pad = [[0, 0], [0, max_len - tf.shape(y)[1]]]
    y = tf.pad(y, y_pad)
    y_pred_pad = [[0, 0], [0, max_len - tf.shape(y_pred)[1]], [0, 0]]
    y_pred = tf.pad(y_pred, y_pred_pad)

    self.compute_loss(x, y, y_pred, None)
    return self.compute_metrics(x, y, y_pred, None)

```

Test your code As a final test, instantiate an encoder–decoder model and use it to decode the example sentence. Check the shapes of the resulting tensors.

```

[24]: def test24():
    src, tgt = example(train_dataset, 42)
    encoder_decoder = EncoderDecoder(src_lookup, tgt_lookup)
    outputs, alphas = encoder_decoder(src)
    print(outputs.shape) # should be (batch_size, max_len, vocabulary_size)
    print(alphas.shape) # should be (batch_size, max_len, src_len)

test24()

```

```
(1, 16, 5000)
```

```
(1, 16, 6)
```

1.4 Part 3: Train a translator

We now have all the pieces to build and train a complete translation system.

1.4.1 Translator class

We first define a class `Translator` that initialises an encoder–decoder model and uses it to translate sentences.

```

[25]: class Translator:
    def __init__(self, src_lookup, tgt_lookup, batch_size=32, **kwargs):
        self.src_lookup = src_lookup
        self.tgt_lookup = tgt_lookup

```

```

self.model = EncoderDecoder(src_lookup, tgt_lookup, **kwargs)
self.tgt_vocab = tgt_lookup.get_vocabulary()
self.eos_index = self.tgt_vocab.index("<eos>")
self.batch_size = batch_size

def compile(self, *args, **kwargs):
    return self.model.compile(*args, **kwargs)

def fit(self, *args, **kwargs):
    return self.model.fit(*args, **kwargs)

def translate(self, sentences, return_alphas=False):
    """This function takes sentences and returns their translation as a
    ↪string.

    `sentences` can be either:
    - A tf.data.Dataset object
    - A list of strings
    """
    if isinstance(sentences, tf.data.Dataset):
        inputs = sentences
    elif isinstance(sentences, (list, tuple)):
        inputs = (
            tf.data.Dataset.from_tensor_slices(
                tf.ragged.constant([x.split() for x in sentences])
            )
            .map(self.src_lookup)
            .padded_batch(min(self.batch_size, len(sentences)))
        )
    else:
        raise ValueError(f"'sentences' should be either a tf.Dataset or a
    ↪list of strings; got: {type(sentences)}")

    outputs, alphas = self.model.predict(inputs, verbose=0)
    outputs = tf.math.argmax(outputs, axis=-1).numpy().tolist()
    try:
        alphas = alphas.numpy().tolist()
    except AttributeError:
        alphas = alphas.tolist()
    generated = []

    for y_pred, alpha in zip(outputs, alphas):
        try:
            eos_idx = y_pred.index(self.eos_index)
            del y_pred[eos_idx:]
            del alpha[eos_idx:]
        except ValueError:

```

```

        pass
        tokens = [self.tgt_vocab[idx] for idx in y_pred if idx > 0]
        tokens = " ".join(tokens)
        if return_alphas:
            generated.append((tokens, alpha))
        else:
            generated.append(tokens)

    return generated

def translate_with_attention(self, sentences):
    return self.translate(sentences, return_alphas=True)

```

The code below shows how this class is supposed to be used (its output will be nonsensical right now, of course, since the model hasn't been trained yet):

```

[26]: translator = Translator(src_lookup, tgt_lookup)
      # Alternative "mini" version of the model for testing:
      #translator = Translator(src_lookup, tgt_lookup, embedding_dim=32,
      ↪hidden_dim=64, batch_size=16, max_len=8)
      translator.translate(['stäng av vattnet .', 'jag älskar friterade bananer .'])

```

```

[26]: ['tiger listener stroll cars considerate climbing nicer short grandfather
      grandfather grandfather burned overworked automatically picked .',
      'doctors wrong spilled mayor carrots cynical upset introduce humanity physics
      bet keeping mixture enjoyable center interested']

```

1.4.2 Evaluation function

As mentioned in the lecture, machine translation systems are typically evaluated using the **BLEU metric**. Here we use the implementation of this metric from the **sacrebleu** library.

```

[27]: from sacrebleu.metrics import BLEU
      bleu_params = dict(effective_order=True, tokenize="none", force=True,
      ↪smooth_method="floor", smooth_value=0.01)
      bleu = BLEU(**bleu_params)

```

If the test sentence is exactly identical to the reference sentence, the score will be 100 (plus/minus potential floating point rounding errors):

```

[28]: bleu.sentence_score("the house is blue .", ["the house is blue ."]).score

```

```

[28]: 100.00000000000004

```

If we change some words, the score will go down, though never below zero:

```

[29]: bleu.sentence_score("the house was red .", ["the house is blue ."]).score

```

```
[29]: 3.9763536438352522
```

Here is a helper function that takes a trained `Translator` model as well as a `Dataset`, runs all sentences through the translator, and computes the BLEU score for the entire dataset:

```
[30]: def compute_bleu(translator, dataset):
    hyp = translator.translate(dataset)
    ref = [
        " ".join(translator.tgt_vocab[idx] for idx in s if idx not in (0,
        ↪ translator.eos_index))
        for s in dataset.unbatch().map(lambda _, x: x).as_numpy_iterator()
    ]
    return bleu.corpus_score(hyp, [ref]).score
```

We want to report the BLEU score on the **validation data**, so let's load this as well:

```
[31]: valid_dataset = load_translation_dataset(src_lookup, tgt_lookup, "en-sv-valid.
    ↪txt")
```

1.4.3 Batching

So far we only tested our code on “batches” with a single sentence. In order to use larger batches, we need to make sure that all of the sentences in a batch have the same length. We achieve this by *padding* the shorter sentences to the length of the longest one. Luckily, the `tf.Dataset` class has a function `padded_batch` that will do this for us. If we provide a `Dataset` for training, Keras won't shuffle the data automatically, so we also have to `shuffle` the dataset explicitly. (For validation, shuffling doesn't matter.)

```
[32]: train_batched = train_dataset.shuffle(512).padded_batch(64)
    valid_batched = valid_dataset.padded_batch(64)
```

1.4.4 Training

Training works as for any other Keras model: we first need to compile the model with the optimizer, loss function, and validation metrics that we want to use.

```
[33]: translator.compile(
    optimizer=keras.optimizers.Adam(learning_rate=2e-3),
    loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True)
)
```

Now it is time to train the system. During training, these diagnostics will be updated periodically: the running average of the training loss; after a full epoch, the loss and the BLEU score on the validation data will be computed and printed.

Let's also define a callback that additionally prints the translation of a sample sentence, *jag saknar min familj* (which should translate into *i miss my family*), every 50 batches:

```
[34]: my_callbacks = [
    keras.callbacks.LambdaCallback(
        on_train_batch_end=lambda b, _: tf.print(" - jag saknar min familj .\n",
        ↪->"), translator.translate(['jag saknar min familj .'])[0]) if b > 0 and b %\n
        ↪50 == 0 else None,
        on_epoch_end=lambda _, l: l.__setitem__("val_bleu",\n
        ↪compute_bleu(translator, valid_batched))
    )
]
```

Task 6: Run the model training Run the following code cells that train the model and evaluate it on the validation data.

Training the translator takes quite a bit of compute power and time. The default number of epochs is 2; however, you may want to try training for longer, or interrupt the training prematurely and use a partially trained model in case you run out of time.

Your submitted notebook must contain output demonstrating at least 20 BLEU points on the validation data.

```
[35]: %%time
try:
    translator.fit(train_batched, epochs=5, validation_data=valid_batched,\n
    ↪callbacks=my_callbacks)
except KeyboardInterrupt:
    pass
```

Epoch 1/5

```
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1746532655.593468 672649 service.cc:148] XLA service 0x7efae0030fc0
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1746532655.593564 672649 service.cc:156] StreamExecutor device
(0): NVIDIA RTX 4000 Ada Generation, Compute Capability 8.9
I0000 00:00:1746532655.656385 672649 device_compiler.h:188] Compiled cluster
using XLA! This line is logged at most once for the lifetime of the process.
```

```
- jag saknar min familj . -> tom ' t ' t .ETA: 15s - loss: 5.2323
- jag saknar min familj . -> i ' t a .] - ETA: 13s - loss: 4.4822
- jag saknar min familj . -> i ' m not .- ETA: 9s - loss: 4.0941
- jag saknar min familj . -> i ' ll go to go to the time .3.8063
- jag saknar min familj . -> i like a <unk> .: 3s - loss: 3.5620
- jag saknar min familj . -> i like my job .A: 0s - loss: 3.3588
322/322 [=====] - 23s 59ms/step - loss: 3.2782 -
val_loss: 4.3596 - val_bleu: 14.6751
```

Epoch 2/5

```
- jag saknar min familj . -> i found my coat . 10s - loss: 2.1575
```

```

- jag saknar min familj . -> i think my bag .: 8s - loss: 2.0670
- jag saknar min familj . -> i ' m going my family .loss: 1.9796
- jag saknar min familj . -> i miss my family .4s - loss: 1.9109
- jag saknar min familj . -> i miss my family .2s - loss: 1.8331
- jag saknar min familj . -> i miss my family .0s - loss: 1.7552
322/322 [=====] - 14s 43ms/step - loss: 1.7236 -
val_loss: 4.6475 - val_bleu: 29.2697
Epoch 3/5
- jag saknar min familj . -> i miss my family .10s - loss: 1.3032
- jag saknar min familj . -> i miss my duty .: 7s - loss: 1.2324
- jag saknar min familj . -> i ' ve got my family . loss: 1.1960
- jag saknar min familj . -> i miss my family .4s - loss: 1.1632
- jag saknar min familj . -> i miss my family .2s - loss: 1.1205
- jag saknar min familj . -> i miss my family .0s - loss: 1.0805
322/322 [=====] - 14s 42ms/step - loss: 1.0634 -
val_loss: 4.9976 - val_bleu: 38.1931
Epoch 4/5
- jag saknar min familj . -> i miss my family .9s - loss: 0.8250
- jag saknar min familj . -> i miss my family .7s - loss: 0.7866
- jag saknar min familj . -> i missed my family family .: 0.7711
- jag saknar min familj . -> i miss my family .4s - loss: 0.7569
- jag saknar min familj . -> i miss my family .2s - loss: 0.7390
- jag saknar min familj . -> i miss my family .0s - loss: 0.7178
322/322 [=====] - 14s 42ms/step - loss: 0.7121 -
val_loss: 5.0942 - val_bleu: 41.9021
Epoch 5/5
- jag saknar min familj . -> i miss my family .9s - loss: 0.5660
- jag saknar min familj . -> i miss my family .7s - loss: 0.5429
- jag saknar min familj . -> i miss my family .6s - loss: 0.5364
- jag saknar min familj . -> i miss my family .4s - loss: 0.5307
- jag saknar min familj . -> i miss my family .2s - loss: 0.5210
- jag saknar min familj . -> i miss my family .0s - loss: 0.5115
322/322 [=====] - 14s 42ms/step - loss: 0.5082 -
val_loss: 5.3574 - val_bleu: 45.1090
CPU times: user 3min 11s, sys: 17.9 s, total: 3min 29s
Wall time: 1min 17s

```

```
[36]: compute_bleu(translator, valid_batched)
```

```
[36]: 45.10901290580661
```

Some notes on the translations If you try out sentences to see their translation (like in the code cell below), you might find some possibly surprising results, such as:

- **Translations that are seemingly nonsensical or have nothing to do with the input.** This might be because the model is undertrained; you could try training for more epochs to see if the translations improve. It's also possible that you tried words or phrases that were just not well-represented in the training data.

- **Translations that have a lot of <unk>s.** This might be due to the words just not being present in the model's vocabulary! Remember you can check this with the vocabularies you created, e.g. "friterade" in `src_vocab`. You could try increasing the vocabulary size and see if the results improve, but this will also increase training time.

Finally, keep in mind that both the dataset and the model itself is quite tiny, as it's optimized for speed and demonstration purposes rather than efficiency!

```
[37]: translator.translate(['jag saknar min familj . ', 'stäng av vattnet .', 'jag_
↪älskar friterade bananer .'])
```

```
[37]: ['i miss my family .', 'close the wheel .', 'i love <unk> bananas .']
```

2 Part 4: Visualising attention

Figure 3 in the paper by [Bahdanau et al. \(2015\)](#) shows some heatmaps of attention weights in selected sentences. In the last problem of this lab, we ask you to inspect attention weights for your trained translation system. We define a function `plot_attention` that visualises the attention weights. The *x*-axis corresponds to the words in the source sentence (Swedish) and the *y*-axis to the generated target sentence (English).

The heatmap colours represent the **strengths of the attention weights**, with *lighter* cells indicating a *higher* attention value, just as in the Bahdanau et al. paper.

```
[38]: import matplotlib.pyplot as plt
import numpy as np

%config InlineBackend.figure_format = 'svg'

plt.style.use('seaborn-v0_8-whitegrid')

def plot_attention(translator, sentence):
    translation, weights = translator.translate_with_attention([sentence])[0]
    weights = np.array(weights)

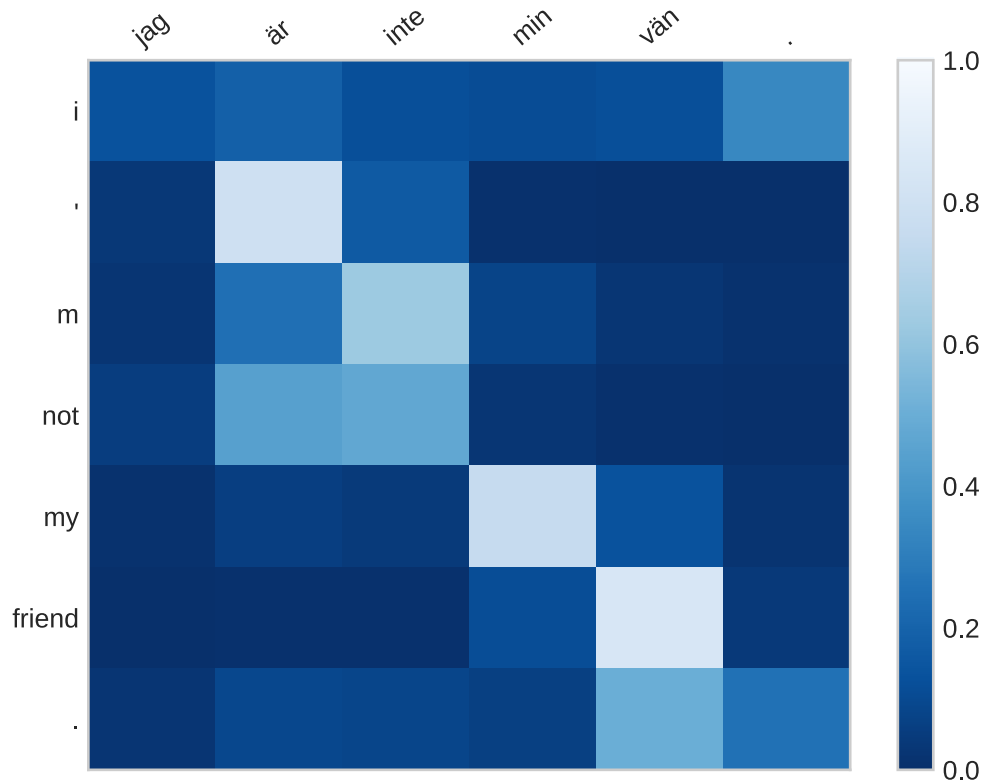
    fig, ax = plt.subplots()
    heatmap = ax.pcolor(weights, cmap='Blues_r', vmin=0., vmax=1.)

    ax.xaxis.tick_top()
    ax.set_xticks(np.arange(weights.shape[1]) + 0.5, minor=False)
    ax.set_yticks(np.arange(weights.shape[0]) + 0.5, minor=False)
    ax.set_xticklabels(sentence.split(), minor=False, rotation=40)
    ax.set_yticklabels(translation.split(), minor=False)
    ax.invert_yaxis()

    plt.colorbar(heatmap)
```

Here is an example.

```
[39]: plot_attention(translator, 'jag är inte min vän .')
```



Task 7: Use these heatmaps to inspect the attention patterns for selected Swedish sentences Try to find sentences for which the model produces reasonably good English translations. If you don't speak Swedish, use sentences from the validation data. It might be interesting to look at examples where the Swedish and the English word order differ substantially.

Based on your exploration, **answer the following questions:**

- What sentences did you try out? What patterns did you spot? Include example heatmaps in your notebook.

We used the Swedish sentence: “jag saknar min familj” (which means “I miss my family”). At the beginning, the model gave strange translations like:

“i hate my car”

“i love my coat”

But after more training, it finally gave the correct one:

“i miss my family”

From the attention heatmap, several patterns are visible: Strong alignments between source and target words appear as brighter squares (closer to white):

“min” aligns strongly with “my”

“vän” aligns well with “friend”

Punctuation match is also entirely accurate, the period at the end aligns well across languages. The matrix is mostly diagonal, which is common for sentence-level translation between languages with similar word order. This diagonal attention suggests good correspondence. Yes, the results are generally what we expected. The attention model appears to be learning token alignments effectively, especially in later epochs.

- Based on what you know about attention, did you expect your results? Was there anything surprising in them?

Yes, the results mostly matched what we expected. The attention model seems to be learning how to align tokens well, especially during the later stages of training.

Early on, the translations didn’t make much sense (like “I love my hair”), but the attention maps still showed meaningful word connections. This means the model had a sense of where to focus, even before it fully understood how to translate properly.

We also noticed some word repetition in the middle of training (like “I already already already...”), which is a common issue in these types of models before they are fully trained.

Congratulations on finishing this lab!