nmt_with_attention

April 18, 2019

1 Neural Machine Translation with Attention

Run in Google Colab

View source on GitHub

This notebook trains a sequence to sequence (seq2seq) model for Spanish to English translation using tf.keras and eager execution. This is an advanced example that assumes some knowledge of sequence to sequence models.

After training the model in this notebook, you will be able to input a Spanish sentence, such as *"£todavia estan en casa?"*, and return the English translation: *"are you still at home?"*

The translation quality is reasonable for a toy example, but the generated attention plot is perhaps more interesting. This shows which parts of the input sentence has the model's attention while translating:

Note: This example takes approximately 10 mintues to run on a single P100 GPU.

In [1]:
```
from __future__ import absolute_import, division, print_function

# Import TensorFlow >= 1.10 and enable eager execution
import tensorflow as tf

tf.enable_eager_execution()

import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

import unicodedata
import re
import numpy as np
import os
import time

print(tf.__version__)
```

```
c:\programs\python\python36\lib\site-packages\h5py\__init__.py:36: FutureWarning: Conversion of
  from ._conv import register_converters as _register_converters
```

```
1.12.0
```

1.1 Download and prepare the dataset

We'll use a language dataset provided by http://www.manythings.org/anki/. This dataset contains language translation pairs in the format:

```
May I borrow this book? £Puedo tomar prestado este libro?
```

There are a variety of languages available, but we'll use the English-Spanish dataset. For convenience, we've hosted a copy of this dataset on Google Cloud, but you can also download your own copy. After downloading the dataset, here are the steps we'll take to prepare the data:

1. Add a *start* and *end* token to each sentence.
2. Clean the sentences by removing special characters.
3. Create a word index and reverse word index (dictionaries mapping from word → id and id → word).
4. Pad each sentence to a maximum length.

```
In [2]: # Download the file
        path_to_zip = tf.keras.utils.get_file(
            'spa-eng.zip', origin='http://download.tensorflow.org/data/spa-eng.zip',
            extract=True)

        path_to_file = os.path.dirname(path_to_zip)+"/spa-eng/spa.txt"
```

```
Downloading data from http://download.tensorflow.org/data/spa-eng.zip
2646016/2638744 [==============================] - 1s 0us/step
```

```
In [3]: # Converts the unicode file to ascii
        def unicode_to_ascii(s):
            return ''.join(c for c in unicodedata.normalize('NFD', s)
                if unicodedata.category(c) != 'Mn')


        def preprocess_sentence(w):
            w = unicode_to_ascii(w.lower().strip())

            # creating a space between a word and the punctuation following it
            # eg: "he is a boy." => "he is a boy ."
            # Reference:- https://stackoverflow.com/questions/3645931/python-padding-punctuation
            w = re.sub(r"([?.!,£])", r" \1 ", w)
            w = re.sub(r'[" "]+', " ", w)

            # replacing everything with space except (a-z, A-Z, ".", "?", "!", ",")
            w = re.sub(r"[^a-zA-Z?.!,£]+", " ", w)
```

```
    w = w.rstrip().strip()

    # adding a start and an end token to the sentence
    # so that the model know when to start and stop predicting.
    w = '<start> ' + w + ' <end>'
    return w
```

In [4]:
```
# 1. Remove the accents
# 2. Clean the sentences
# 3. Return word pairs in the format: [ENGLISH, SPANISH]
def create_dataset(path, num_examples):
    lines = open(path, encoding='UTF-8').read().strip().split('\n')

    word_pairs = [[preprocess_sentence(w) for w in l.split('\t')]  for l in lines[:num_e

    return word_pairs
```

In [5]:
```
# This class creates a word -> index mapping (e.g,. "dad" -> 5) and vice-versa
# (e.g., 5 -> "dad") for each language,
class LanguageIndex():
  def __init__(self, lang):
    self.lang = lang
    self.word2idx = {}
    self.idx2word = {}
    self.vocab = set()

    self.create_index()

  def create_index(self):
    for phrase in self.lang:
      self.vocab.update(phrase.split(' '))

    self.vocab = sorted(self.vocab)

    self.word2idx['<pad>'] = 0
    for index, word in enumerate(self.vocab):
      self.word2idx[word] = index + 1

    for word, index in self.word2idx.items():
      self.idx2word[index] = word
```

In [6]:
```
def max_length(tensor):
    return max(len(t) for t in tensor)


def load_dataset(path, num_examples):
    # creating cleaned input, output pairs
    pairs = create_dataset(path, num_examples)
```

```
    # index language using the class defined above
    inp_lang = LanguageIndex(sp for en, sp in pairs)
    targ_lang = LanguageIndex(en for en, sp in pairs)

    # Vectorize the input and target languages

    # Spanish sentences
    input_tensor = [[inp_lang.word2idx[s] for s in sp.split(' ')] for en, sp in pairs]

    # English sentences
    target_tensor = [[targ_lang.word2idx[s] for s in en.split(' ')] for en, sp in pairs]

    # Calculate max_length of input and output tensor
    # Here, we'll set those to the longest sentence in the dataset
    max_length_inp, max_length_tar = max_length(input_tensor), max_length(target_tensor)

    # Padding the input and output tensor to the maximum length
    input_tensor = tf.keras.preprocessing.sequence.pad_sequences(input_tensor,
                                                                 maxlen=max_length_inp,
                                                                 padding='post')

    target_tensor = tf.keras.preprocessing.sequence.pad_sequences(target_tensor,
                                                                  maxlen=max_length_tar,
                                                                  padding='post')

    return input_tensor, target_tensor, inp_lang, targ_lang, max_length_inp, max_length_
```

1.1.1 Limit the size of the dataset to experiment faster (optional)

Training on the complete dataset of >100,000 sentences will take a long time. To train faster, we can limit the size of the dataset to 30,000 sentences (of course, translation quality degrades with less data):

```
In [7]: # Try experimenting with the size of that dataset
        num_examples = 30000
        input_tensor, target_tensor, inp_lang, targ_lang, max_length_inp, max_length_targ = load
```

```
In [8]: # Creating training and validation sets using an 80-20 split
        input_tensor_train, input_tensor_val, target_tensor_train, target_tensor_val = train_tes

        # Show length
        len(input_tensor_train), len(target_tensor_train), len(input_tensor_val), len(target_ten
```

```
Out[8]: (24000, 24000, 6000, 6000)
```

1.1.2 Create a tf.data dataset

```
In [9]: BUFFER_SIZE = len(input_tensor_train)
        BATCH_SIZE = 64
```

```
N_BATCH = BUFFER_SIZE//BATCH_SIZE
embedding_dim = 256
units = 1024
vocab_inp_size = len(inp_lang.word2idx)
vocab_tar_size = len(targ_lang.word2idx)

dataset = tf.data.Dataset.from_tensor_slices((input_tensor_train, target_tensor_train)).
dataset = dataset.batch(BATCH_SIZE, drop_remainder=True)
```

1.2 Write the encoder and decoder model

Here, we'll implement an encoder-decoder model with attention which you can read about in the TensorFlow Neural Machine Translation (seq2seq) tutorial. This example uses a more recent set of APIs. This notebook implements the attention equations from the seq2seq tutorial. The following diagram shows that each input words is assigned a weight by the attention mechanism which is then used by the decoder to predict the next word in the sentence.

The input is put through an encoder model which gives us the encoder output of shape *(batch_size, max_length, hidden_size)* and the encoder hidden state of shape *(batch_size, hidden_size)*.

Here are the equations that are implemented:

We're using *Bahdanau attention*. Lets decide on notation before writing the simplified form:

- FC = Fully connected (dense) layer
- EO = Encoder output
- H = hidden state
- X = input to the decoder

And the pseudo-code:

- `score = FC(tanh(FC(EO) + FC(H)))`
- `attention weights = softmax(score, axis = 1)`. Softmax by default is applied on the last axis but here we want to apply it on the *1st axis*, since the shape of score is *(batch_size, max_length, 1)*. `Max_length` is the length of our input. Since we are trying to assign a weight to each input, softmax should be applied on that axis.
- `context vector = sum(attention weights * EO, axis = 1)`. Same reason as above for choosing axis as 1.
- `embedding output` = The input to the decoder X is passed through an embedding layer.
- `merged vector = concat(embedding output, context vector)`
- This merged vector is then given to the GRU

The shapes of all the vectors at each step have been specified in the comments in the code:

```
In [10]: def gru(units):
           # If you have a GPU, we recommend using CuDNNGRU(provides a 3x speedup than GRU)
           # the code automatically does that.
           if tf.test.is_gpu_available():
             return tf.keras.layers.CuDNNGRU(units,
                                              return_sequences=True,
                                              return_state=True,
                                              recurrent_initializer='glorot_uniform')
```

```
        else:
          return tf.keras.layers.GRU(units,
                                     return_sequences=True,
                                     return_state=True,
                                     recurrent_activation='sigmoid',
                                     recurrent_initializer='glorot_uniform')

In [11]: class Encoder(tf.keras.Model):
            def __init__(self, vocab_size, embedding_dim, enc_units, batch_sz):
                super(Encoder, self).__init__()
                self.batch_sz = batch_sz
                self.enc_units = enc_units
                self.embedding = tf.keras.layers.Embedding(vocab_size, embedding_dim)
                self.gru = gru(self.enc_units)

            def call(self, x, hidden):
                x = self.embedding(x)
                output, state = self.gru(x, initial_state = hidden)
                return output, state

            def initialize_hidden_state(self):
                return tf.zeros((self.batch_sz, self.enc_units))

In [13]: class Decoder(tf.keras.Model):
            def __init__(self, vocab_size, embedding_dim, dec_units, batch_sz):
                super(Decoder, self).__init__()
                self.batch_sz = batch_sz
                self.dec_units = dec_units
                self.embedding = tf.keras.layers.Embedding(vocab_size, embedding_dim)
                self.gru = gru(self.dec_units)
                self.fc = tf.keras.layers.Dense(vocab_size)

                # used for attention
                self.W1 = tf.keras.layers.Dense(self.dec_units)
                self.W2 = tf.keras.layers.Dense(self.dec_units)
                self.V = tf.keras.layers.Dense(1)

            def call(self, x, hidden, enc_output):
                # enc_output shape == (batch_size, max_length, hidden_size)

                # hidden shape == (batch_size, hidden size)
                # hidden_with_time_axis shape == (batch_size, 1, hidden size)
                # we are doing this to perform addition to calculate the score
                hidden_with_time_axis = tf.expand_dims(hidden, 1)

                # score shape == (batch_size, max_length, 1)
                # we get 1 at the last axis because we are applying tanh(FC(EO) + FC(H)) to sel
                score = self.V(tf.nn.tanh(self.W1(enc_output) + self.W2(hidden_with_time_axis))
```

```
        # attention_weights shape == (batch_size, max_length, 1)
        attention_weights = tf.nn.softmax(score, axis=1)

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

        # x shape after passing through embedding == (batch_size, 1, embedding_dim)
        x = self.embedding(x)

        # x shape after concatenation == (batch_size, 1, embedding_dim + hidden_size)
        x = tf.concat([tf.expand_dims(context_vector, 1), x], axis=-1)

        # passing the concatenated vector to the GRU
        output, state = self.gru(x)

        # output shape == (batch_size * 1, hidden_size)
        output = tf.reshape(output, (-1, output.shape[2]))

        # output shape == (batch_size * 1, vocab)
        x = self.fc(output)

        return x, state, attention_weights

    def initialize_hidden_state(self):
        return tf.zeros((self.batch_sz, self.dec_units))
```

```
In [14]: encoder = Encoder(vocab_inp_size, embedding_dim, units, BATCH_SIZE)
         decoder = Decoder(vocab_tar_size, embedding_dim, units, BATCH_SIZE)
```

1.3 Define the optimizer and the loss function

```
In [15]: optimizer = tf.train.AdamOptimizer()
```

```
         def loss_function(real, pred):
           mask = 1 - np.equal(real, 0)
           loss_ = tf.nn.sparse_softmax_cross_entropy_with_logits(labels=real, logits=pred) * ma
           return tf.reduce_mean(loss_)
```

1.4 Checkpoints (Object-based saving)

```
In [16]: checkpoint_dir = './training_checkpoints'
         checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
         checkpoint = tf.train.Checkpoint(optimizer=optimizer,
                                          encoder=encoder,
                                          decoder=decoder)
```

1.5 Training

1. Pass the *input* through the *encoder* which return *encoder output* and the *encoder hidden state*.
2. The encoder output, encoder hidden state and the decoder input (which is the *start token*) is passed to the decoder.
3. The decoder returns the *predictions* and the *decoder hidden state*.
4. The decoder hidden state is then passed back into the model and the predictions are used to calculate the loss.
5. Use *teacher forcing* to decide the next input to the decoder.
6. *Teacher forcing* is the technique where the *target word* is passed as the *next input* to the decoder.
7. The final step is to calculate the gradients and apply it to the optimizer and backpropagate.

In [18]:
```
EPOCHS = 10

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

    hidden = encoder.initialize_hidden_state()
    total_loss = 0

    for (batch, (inp, targ)) in enumerate(dataset):
        loss = 0

        with tf.GradientTape() as tape:
            enc_output, enc_hidden = encoder(inp, hidden)

            dec_hidden = enc_hidden

            dec_input = tf.expand_dims([targ_lang.word2idx['<start>']] * BATCH_SIZE, 1)

            # Teacher forcing - feeding the target as the next input
            for t in range(1, targ.shape[1]):
                # passing enc_output to the decoder
                predictions, dec_hidden, _ = decoder(dec_input, dec_hidden, enc_output)

                loss += loss_function(targ[:, t], predictions)

                # using teacher forcing
                dec_input = tf.expand_dims(targ[:, t], 1)

        batch_loss = (loss / int(targ.shape[1]))

        total_loss += batch_loss

        variables = encoder.variables + decoder.variables

        gradients = tape.gradient(loss, variables)

        optimizer.apply_gradients(zip(gradients, variables))
```

```
            if batch % 100 == 0:
                print('Epoch {} Batch {} Loss {:.4f}'.format(epoch + 1,
                                                             batch,
                                                             batch_loss.numpy()))
        # saving (checkpoint) the model every 2 epochs
        if (epoch + 1) % 2 == 0:
          checkpoint.save(file_prefix = checkpoint_prefix)

        print('Epoch {} Loss {:.4f}'.format(epoch + 1,
                                            total_loss / N_BATCH))
        print('Time taken for 1 epoch {} sec\n'.format(time.time() - start))
```

```
Epoch 1 Batch 0 Loss 1.1319
Epoch 1 Batch 100 Loss 1.0521
Epoch 1 Batch 200 Loss 0.9302
Epoch 1 Batch 300 Loss 0.8515
Epoch 1 Loss 0.9603
Time taken for 1 epoch 251.64528918266296 sec

Epoch 2 Batch 0 Loss 0.5634
Epoch 2 Batch 100 Loss 0.6927
Epoch 2 Batch 200 Loss 0.7160
Epoch 2 Batch 300 Loss 0.6850
Epoch 2 Loss 0.6514
Time taken for 1 epoch 245.27540397644043 sec

Epoch 3 Batch 0 Loss 0.3857
Epoch 3 Batch 100 Loss 0.4276
Epoch 3 Batch 200 Loss 0.5119
Epoch 3 Batch 300 Loss 0.3729
Epoch 3 Loss 0.4408
Time taken for 1 epoch 240.26327800750732 sec

Epoch 4 Batch 0 Loss 0.2854
Epoch 4 Batch 100 Loss 0.3098
Epoch 4 Batch 200 Loss 0.2214
Epoch 4 Batch 300 Loss 0.3087
Epoch 4 Loss 0.3066
Time taken for 1 epoch 247.301167011261 sec

Epoch 5 Batch 0 Loss 0.2182
Epoch 5 Batch 100 Loss 0.2381
Epoch 5 Batch 200 Loss 0.2221
Epoch 5 Batch 300 Loss 0.2033
Epoch 5 Loss 0.2190
Time taken for 1 epoch 238.82354092597961 sec
```

```
Epoch 6 Batch 0 Loss 0.1295
Epoch 6 Batch 100 Loss 0.1240
Epoch 6 Batch 200 Loss 0.1899
Epoch 6 Batch 300 Loss 0.1923
Epoch 6 Loss 0.1623
Time taken for 1 epoch 235.6641595363617 sec

Epoch 7 Batch 0 Loss 0.1125
Epoch 7 Batch 100 Loss 0.1200
Epoch 7 Batch 200 Loss 0.0880
Epoch 7 Batch 300 Loss 0.1359
Epoch 7 Loss 0.1262
Time taken for 1 epoch 230.63460493087769 sec

Epoch 8 Batch 0 Loss 0.0738
Epoch 8 Batch 100 Loss 0.0893
Epoch 8 Batch 200 Loss 0.0983
Epoch 8 Batch 300 Loss 0.1121
Epoch 8 Loss 0.1025
Time taken for 1 epoch 235.62626481056213 sec

Epoch 9 Batch 0 Loss 0.0927
Epoch 9 Batch 100 Loss 0.0923
Epoch 9 Batch 200 Loss 0.0903
Epoch 9 Batch 300 Loss 0.1034
Epoch 9 Loss 0.0880
Time taken for 1 epoch 232.24031019210815 sec

Epoch 10 Batch 0 Loss 0.0621
Epoch 10 Batch 100 Loss 0.0919
Epoch 10 Batch 200 Loss 0.0833
Epoch 10 Batch 300 Loss 0.1079
Epoch 10 Loss 0.0777
Time taken for 1 epoch 236.94872879981995 sec
```

1.6 Translate

- The evaluate function is similar to the training loop, except we don't use *teacher forcing* here. The input to the decoder at each time step is its previous predictions along with the hidden state and the encoder output.
- Stop predicting when the model predicts the *end token*.
- And store the *attention weights for every time step*.

Note: The encoder output is calculated only once for one input.

```
In [19]: def evaluate(sentence, encoder, decoder, inp_lang, targ_lang, max_length_inp, max_lengt
             attention_plot = np.zeros((max_length_targ, max_length_inp))
```

```
    sentence = preprocess_sentence(sentence)

    inputs = [inp_lang.word2idx[i] for i in sentence.split(' ')]
    inputs = tf.keras.preprocessing.sequence.pad_sequences([inputs], maxlen=max_length_
    inputs = tf.convert_to_tensor(inputs)

    result = ''

    hidden = [tf.zeros((1, units))]
    enc_out, enc_hidden = encoder(inputs, hidden)

    dec_hidden = enc_hidden
    dec_input = tf.expand_dims([targ_lang.word2idx['<start>']], 0)

    for t in range(max_length_targ):
        predictions, dec_hidden, attention_weights = decoder(dec_input, dec_hidden, enc

        # storing the attention weigths to plot later on
        attention_weights = tf.reshape(attention_weights, (-1, ))
        attention_plot[t] = attention_weights.numpy()

        predicted_id = tf.argmax(predictions[0]).numpy()

        result += targ_lang.idx2word[predicted_id] + ' '

        if targ_lang.idx2word[predicted_id] == '<end>':
            return result, sentence, attention_plot

        # the predicted ID is fed back into the model
        dec_input = tf.expand_dims([predicted_id], 0)

    return result, sentence, attention_plot
```

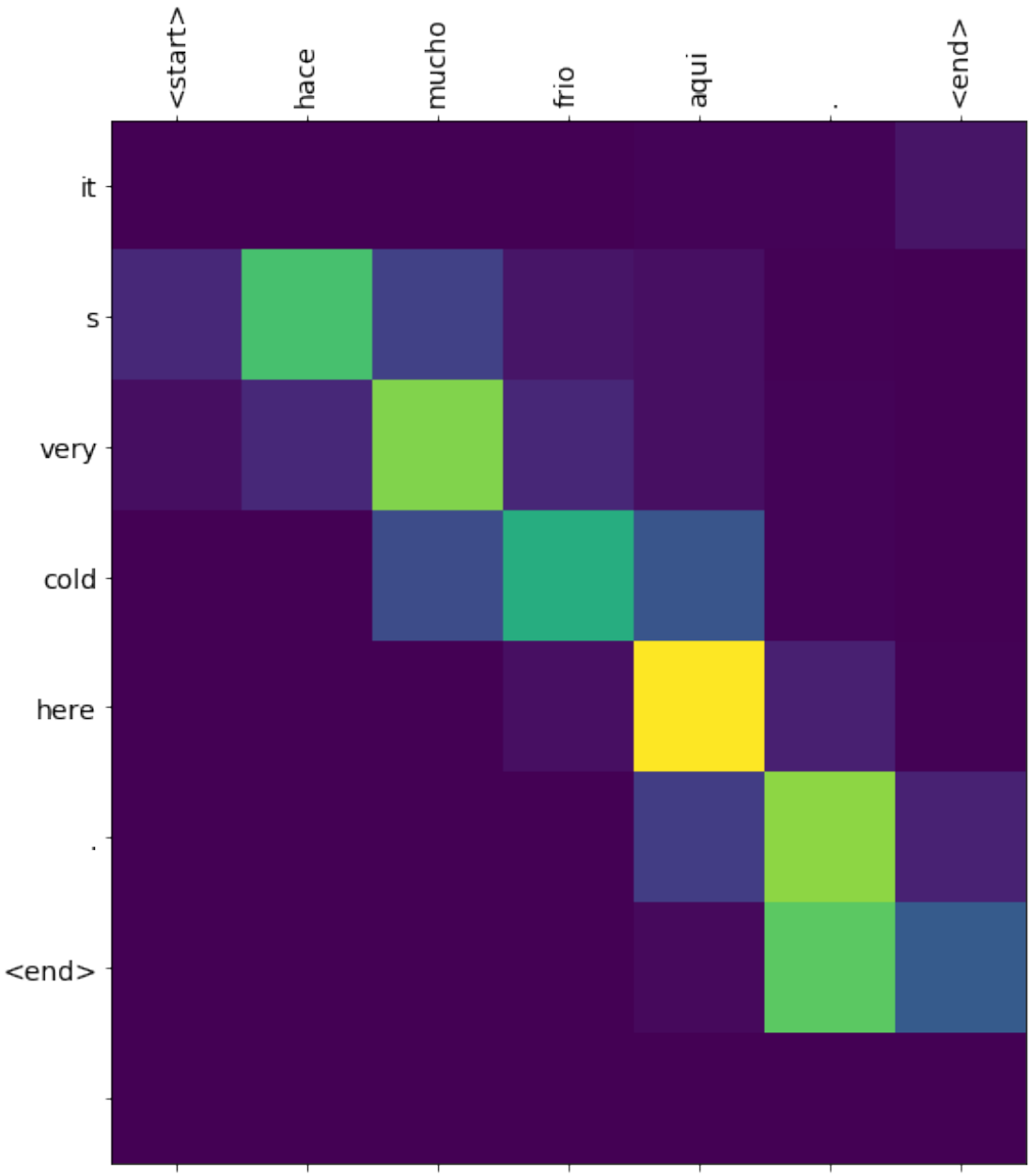
In [20]:
```
# function for plotting the attention weights
def plot_attention(attention, sentence, predicted_sentence):
    fig = plt.figure(figsize=(10,10))
    ax = fig.add_subplot(1, 1, 1)
    ax.matshow(attention, cmap='viridis')

    fontdict = {'fontsize': 14}

    ax.set_xticklabels([''] + sentence, fontdict=fontdict, rotation=90)
    ax.set_yticklabels([''] + predicted_sentence, fontdict=fontdict)

    plt.show()
```

In [21]:
```
def translate(sentence, encoder, decoder, inp_lang, targ_lang, max_length_inp, max_leng
    result, sentence, attention_plot = evaluate(sentence, encoder, decoder, inp_lang, t
```

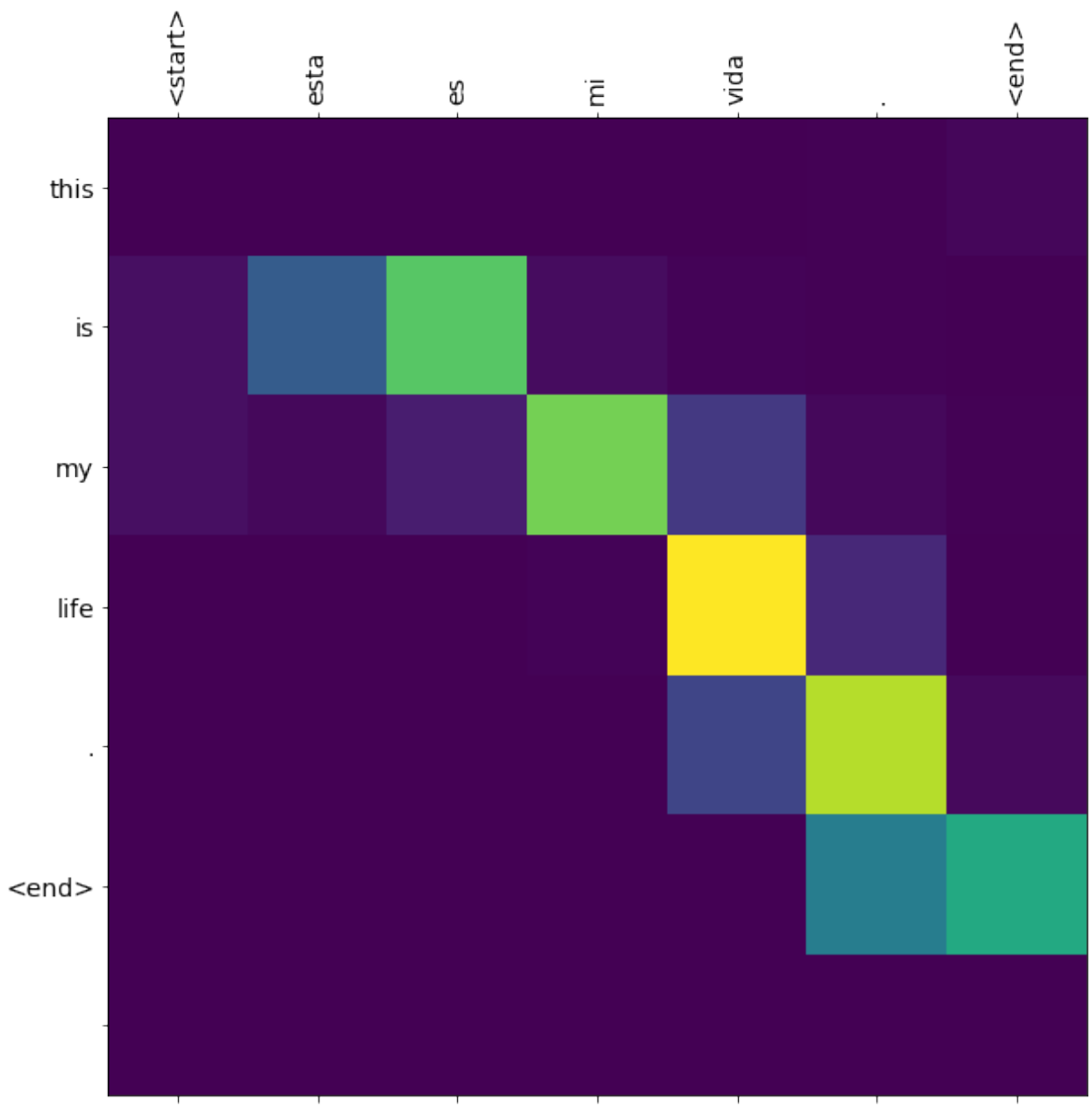
```
            print('Input: {}'.format(sentence))
            print('Predicted translation: {}'.format(result))

            attention_plot = attention_plot[:len(result.split(' ')), :len(sentence.split(' '))]
            plot_attention(attention_plot, sentence.split(' '), result.split(' '))
```

1.7 Restore the latest checkpoint and test

```
In [22]: # restoring the latest checkpoint in checkpoint_dir
         checkpoint.restore(tf.train.latest_checkpoint(checkpoint_dir))

Out[22]: <tensorflow.python.training.checkpointable.util.CheckpointLoadStatus at 0x180806fab70>

In [23]: translate(u'hace mucho frio aqui.', encoder, decoder, inp_lang, targ_lang, max_length_i

Input: <start> hace mucho frio aqui . <end>
Predicted translation: it s very cold here . <end>
```

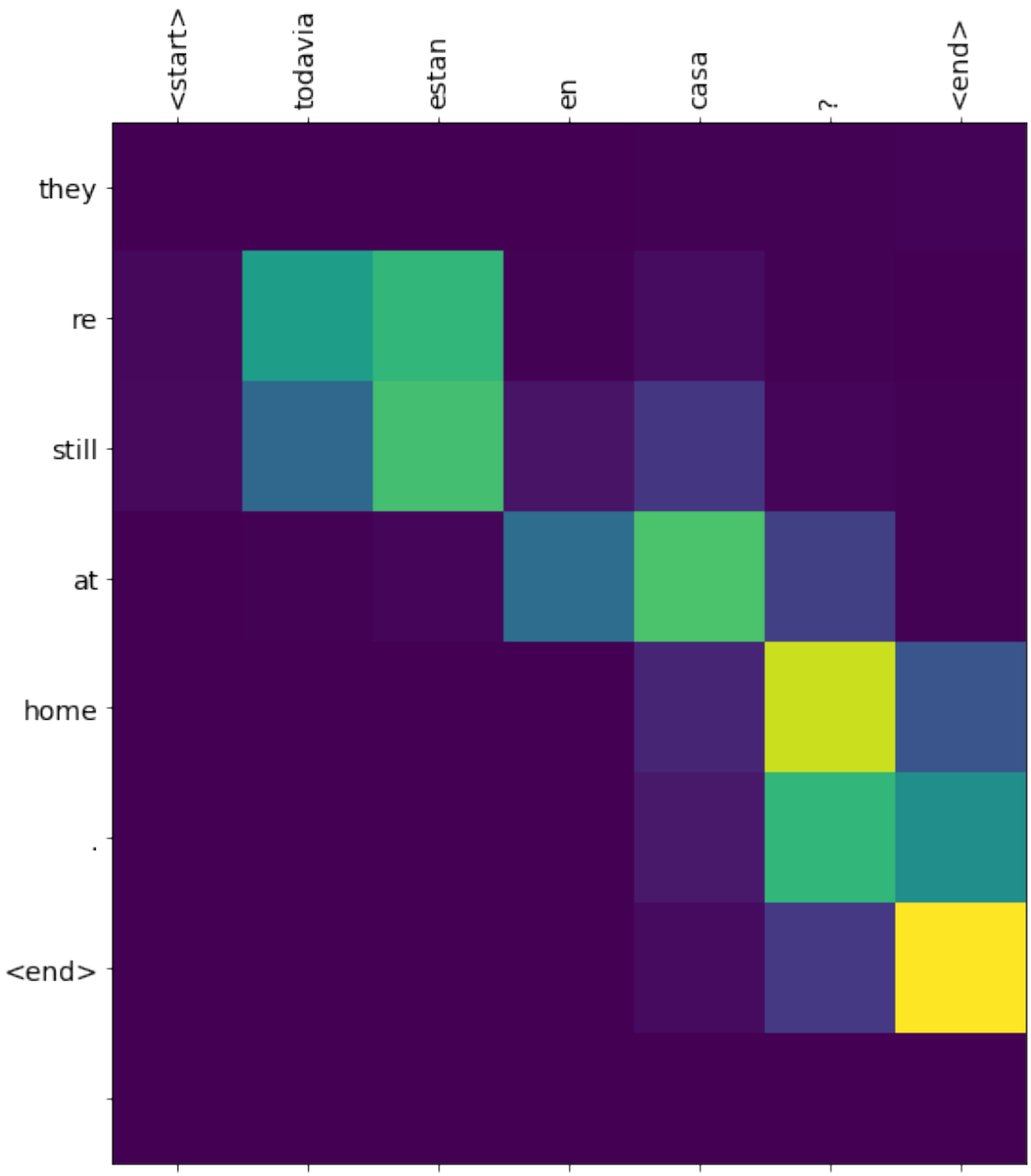



```
In [24]: translate(u'esta es mi vida.', encoder, decoder, inp_lang, targ_lang, max_length_inp, m

Input: <start> esta es mi vida . <end>
Predicted translation: this is my life . <end>
```



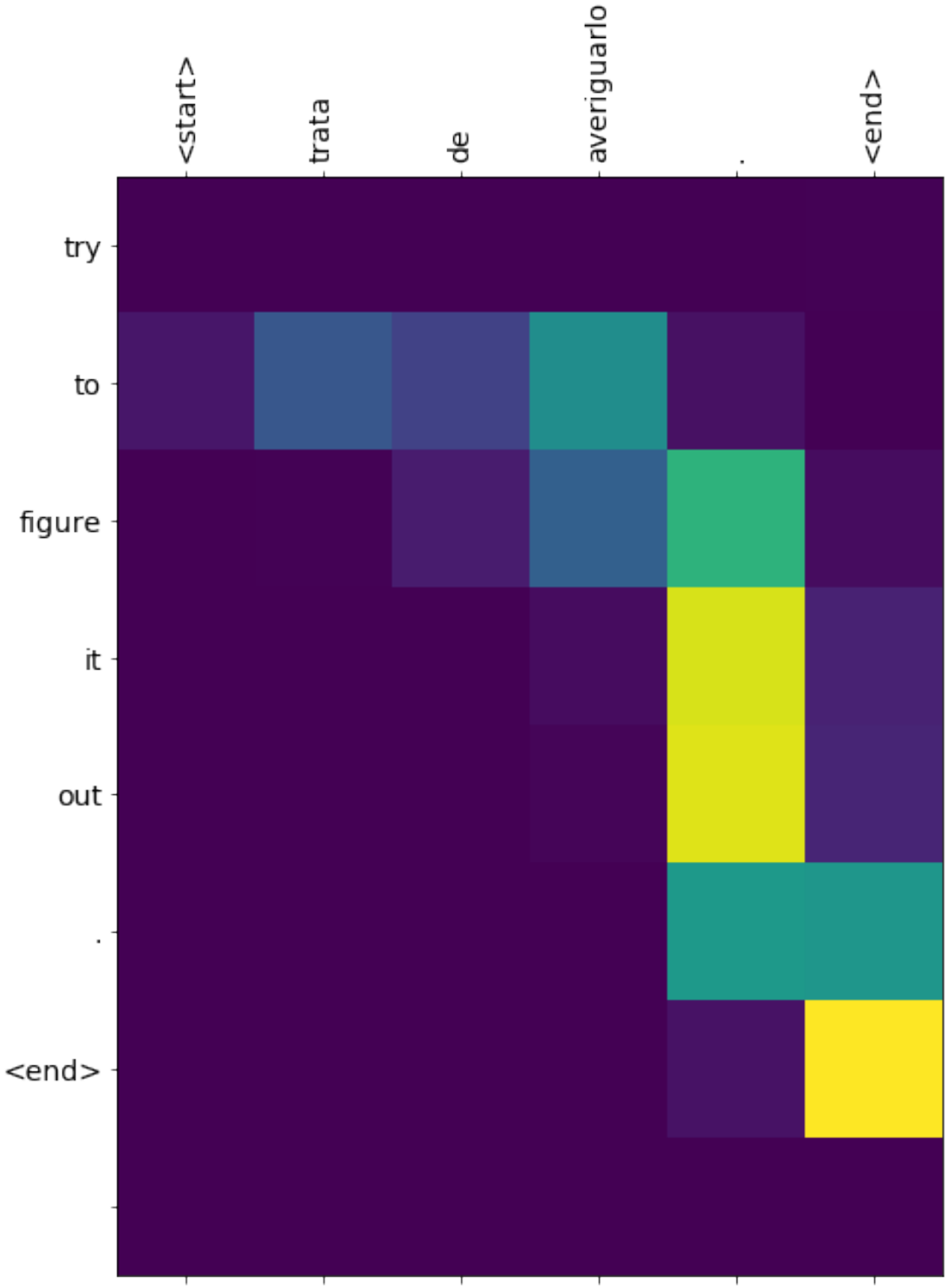

```
In [25]: translate(u'todavia estan en casa?', encoder, decoder, inp_lang, targ_lang, max_length_
```

```
Input: <start> todavia estan en casa ? <end>
Predicted translation: they re still at home . <end>
```



In [26]:
```
# wrong translation
translate(u'trata de averiguarlo.', encoder, decoder, inp_lang, targ_lang, max_length_i
```

```
Input: <start> trata de averiguarlo . <end>
Predicted translation: try to figure it out . <end>
```


<start>
trata
de
averiguarlo
.
<end>
try
to
figure
it
out
.
<end>

1.8 Next steps

- Download a different dataset to experiment with translations, for example, English to German, or English to French.
- Experiment with training on a larger dataset, or using more epochs