Language Translator

Introduction

We'll build a sequence-to-sequence Transformer model, which we'll train on an English-to-Spanish machine translation task.

You'll learn how to:

- Vectorize text using the Keras TextVectorization layer.
- Implement a TransformerEncoder layer, a TransformerDecoder layer, and a PositionalEmbedding layer.
- Prepare data for training a sequence-to-sequence model.
- Use the trained model to generate translations of never-seen-before input sentences (sequence-to-sequence inference).

Downloading the data

The code below shows the exact process of downloading the dataset.

```
text_file = keras.utils.get_file(
    fname="spa-eng.zip",
    origin="http://storage.googleapis.com/download.tensorflow.org/data/spa-eng.zip",
    extract=True,
)
text_file = pathlib.Path(text_file).parent / "spa-eng" / "spa.txt"
```

Parsing the data

Each line contains an English sentence and its corresponding Spanish sentence. The English sentence is the source sequence and Spanish one is the target sequence. We prepend the token "[start]" and we append the token "[end]" to the Spanish sentence.

```
with open(text_file) as f:
    lines = f.read().split("\n")[:-1]
text_pairs = []
for line in lines:
    eng, spa = line.split("\t")
    spa = "[start] " + spa + " [end]"
    text_pairs.append((eng, spa))
```

Here's what our sentence pairs look like:

```
for _ in range(5):
    print(random.choice(text_pairs))
```

```
("You can dance, can't you?", '[start] Puedes bailar, ¿verdad? [end]')
('I passed by her house yesterday.', '[start] Me pasé por su casa ayer. [end]')
('I like tulips.', '[start] Me gustan los tulipanes. [end]')
('He is fluent in French.', '[start] Habla un francés fluido. [end]')
('Tom asked me what I had been doing.', '[start] Tom me preguntó qué había estado haciendo. [e
```

splitting the sentence pairs into a training set, a validation set, and a test set:

```
random.shuffle(text_pairs)
num_val_samples = int(0.15 * len(text_pairs))
num_train_samples = len(text_pairs) - 2 * num_val_samples
train_pairs = text_pairs[:num_train_samples]
val_pairs = text_pairs[num_train_samples : num_train_samples + num_val_samples]
test_pairs = text_pairs[num_train_samples + num_val_samples :]

print(f"{len(text_pairs)} total pairs")
print(f"{len(train_pairs)} training pairs")
print(f"{len(val_pairs)} validation pairs")
print(f"{len(test_pairs)} test pairs")
```

Resulting output fot the above code:

```
118964 total pairs
83276 training pairs
17844 validation pairs
17844 test pairs
```

Vectorizing the text data:

We'll use two instances of the TextVectorization layer to vectorize the text data (one for English and one for Spanish), that is to say, to turn the original strings into integer sequences where each integer represents the index of a word in a vocabulary.

The English layer will use the default string standardization (strip punctuation characters) and splitting scheme (split on whitespace), while the Spanish layer will use a custom standardization, where we add the character "¿" to the set of punctuation characters to be stripped.

```
strip_chars = string.punctuation + "¿"
strip_chars = strip_chars.replace("[", "")
strip_chars = strip_chars.replace("]", "")

vocab_size = 15000
sequence_length = 20
batch_size = 64


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


eng_vectorization = TextVectorization(
    max_tokens=vocab_size, output_mode="int", output_sequence_length=sequence_length,
)
spa_vectorization = TextVectorization(
    max_tokens=vocab_size,
    output_mode="int",
    output_sequence_length=sequence_length + 1,
    standardize=custom_standardization,
)
train_eng_texts = [pair[0] for pair in train_pairs]
train_spa_texts = [pair[1] for pair in train_pairs]
eng_vectorization.adapt(train_eng_texts)
spa_vectorization.adapt(train_spa_texts)
```

Now next step is to format our datasets.

At each training step, the model will seek to predict target words N+1 (and beyond) using the source sentence and the target words 0 to N.

As such, the training dataset will yield a tuple (inputs, targets), where:

- inputs is a dictionary with the keys encoder_inputs and decoder_inputs. encoder_inputs is the vectorized source sentence and encoder_inputs is the target sentence "so far", that is to say, the words 0 to N used to predict word N+1 (and beyond) in the target sentence.
- target is the target sentence offset by one step: it provides the next words in the target sentence -- what the model will try to predict.

```
def format_dataset(eng, spa):
    eng = eng_vectorization(eng)
    spa = spa_vectorization(spa)
    return ({"encoder_inputs": eng, "decoder_inputs": spa[:, :-1],}, spa[:, 1:])


def make_dataset(pairs):
    eng_texts, spa_texts = zip(*pairs)
    eng_texts = list(eng_texts)
    spa_texts = list(spa_texts)
    dataset = tf.data.Dataset.from_tensor_slices((eng_texts, spa_texts))
    dataset = dataset.batch(batch_size)
    dataset = dataset.map(format_dataset)
    return dataset.shuffle(2048).prefetch(16).cache()


train_ds = make_dataset(train_pairs)
val_ds = make_dataset(val_pairs)
```

sequence shapes:

```
for inputs, targets in train_ds.take(1):
    print(f'inputs["encoder_inputs"].shape: {inputs["encoder_inputs"].shape}')
    print(f'inputs["decoder_inputs"].shape: {inputs["decoder_inputs"].shape}')
    print(f"targets.shape: {targets.shape}")
```

```
inputs["encoder_inputs"].shape: (64, 20)
inputs["decoder_inputs"].shape: (64, 20)
targets.shape: (64, 20)
```

Building the model

Our sequence-to-sequence Transformer consists of a TransformerEncoder and a TransformerDecoder chained together. To make the model aware of word order, we also use a PositionalEmbedding layer.

The source sequence will be pass to the TransformerEncoder, which will produce a new representation of it. This new representation will then be passed to the TransformerDecoder, together with the target sequence so far (target words 0 to N). The TransformerDecoder will then seek to predict the next words in the target sequence (N+1 and beyond).

A key detail that makes this possible is causal masking (see method get_causal_attention_mask() on the TransformerDecoder). The TransformerDecoder sees the entire sequences at once, and thus we must make sure that it only uses information from target tokens 0 to N when predicting token N+1 (otherwise, it could use information from the future, which would result in a model that cannot be used at inference time).

Transformer Encoder:

```
class TransformerEncoder(layers.Layer):
    def __init__(self, embed_dim, dense_dim, num_heads, **kwargs):
        super(TransformerEncoder, self).__init__(**kwargs)
        self.embed_dim = embed_dim
        self.dense_dim = dense_dim
        self.num_heads = num_heads
        self.attention = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim
        )
        self.dense_proj = keras.Sequential(
            [layers.Dense(dense_dim, activation="relu"), layers.Dense(embed_dim),]
        )
        self.layernorm_1 = layers.LayerNormalization()
        self.layernorm_2 = layers.LayerNormalization()
        self.supports_masking = True

    def call(self, inputs, mask=None):
        if mask is not None:
            padding_mask = tf.cast(mask[:, tf.newaxis, tf.newaxis, :], dtype="int32")
        attention_output = self.attention(
            query=inputs, value=inputs, key=inputs, attention_mask=padding_mask
        )
        proj_input = self.layernorm_1(inputs + attention_output)
        proj_output = self.dense_proj(proj_input)
        return self.layernorm_2(proj_input + proj_output)
```

Positional Embedding:

```
class PositionalEmbedding(layers.Layer):
    def __init__(self, sequence_length, vocab_size, embed_dim, **kwargs):
        super(PositionalEmbedding, self).__init__(**kwargs)
        self.token_embeddings = layers.Embedding(
            input_dim=vocab_size, output_dim=embed_dim
        )
        self.position_embeddings = layers.Embedding(
            input_dim=sequence_length, output_dim=embed_dim
        )
        self.sequence_length = sequence_length
        self.vocab_size = vocab_size
        self.embed_dim = embed_dim

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

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

Transformer Decoder:

```
class TransformerDecoder(layers.Layer):
    def __init__(self, embed_dim, latent_dim, num_heads, **kwargs):
        super(TransformerDecoder, self).__init__(**kwargs)
        self.embed_dim = embed_dim
        self.latent_dim = latent_dim
        self.num_heads = num_heads
        self.attention_1 = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim
        )
        self.attention_2 = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=embed_dim
        )
        self.dense_proj = keras.Sequential(
            [layers.Dense(latent_dim, activation="relu"), layers.Dense(embed_dim),]
        )
        self.layernorm_1 = layers.LayerNormalization()
        self.layernorm_2 = layers.LayerNormalization()
        self.layernorm_3 = layers.LayerNormalization()
        self.supports_masking = True
```

Defining Call inside Transformer Decoder class :

```
def call(self, inputs, encoder_outputs, mask=None):
    causal_mask = self.get_causal_attention_mask(inputs)
    if mask is not None:
        padding_mask = tf.cast(mask[:, tf.newaxis, :], dtype="int32")
        padding_mask = tf.minimum(padding_mask, causal_mask)

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

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

    proj_output = self.dense_proj(out_2)
    return self.layernorm_3(out_2 + proj_output)
```

Defining get_causal_attention_mask inside Transformer Decoder class :

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

Next step is assembling the end-to-end model:

```
embed_dim = 256
latent_dim = 2048
num_heads = 8

encoder_inputs = keras.Input(shape=(None,), dtype="int64", name="encoder_inputs")
x = PositionalEmbedding(sequence_length, vocab_size, embed_dim)(encoder_inputs)
encoder_outputs = TransformerEncoder(embed_dim, latent_dim, num_heads)(x)
encoder = keras.Model(encoder_inputs, encoder_outputs)

decoder_inputs = keras.Input(shape=(None,), dtype="int64", name="decoder_inputs")
encoded_seq_inputs = keras.Input(shape=(None, embed_dim), name="decoder_state_inputs")
x = PositionalEmbedding(sequence_length, vocab_size, embed_dim)(decoder_inputs)
x = TransformerDecoder(embed_dim, latent_dim, num_heads)(x, encoded_seq_inputs)
x = layers.Dropout(0.5)(x)
decoder_outputs = layers.Dense(vocab_size, activation="softmax")(x)
decoder = keras.Model([decoder_inputs, encoded_seq_inputs], decoder_outputs)

decoder_outputs = decoder([decoder_inputs, encoder_outputs])
transformer = keras.Model(
    [encoder_inputs, decoder_inputs], decoder_outputs, name="transformer"
)
```

Training our model

We'll use accuracy as a quick way to monitor training progress on the validation data. Note that machine translation typically uses BLEU scores as well as other metrics, rather than accuracy.

Here to get the model to actually converge you should train for at least 30 epochs.

```
epochs = 1  # This should be at least 30 for convergence

transformer.summary()
transformer.compile(
    "rmsprop", loss="sparse_categorical_crossentropy", metrics=["accuracy"]
)
transformer.fit(train_ds, epochs=epochs, validation_data=val_ds)
```

```
Model: "transformer"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
encoder_inputs (InputLayer)     [(None, None)]       0
__________________________________________________________________________________________________
positional_embedding (Positiona (None, None, 256)    3845120     encoder_inputs[0][0]
__________________________________________________________________________________________________
decoder_inputs (InputLayer)     [(None, None)]       0
__________________________________________________________________________________________________
transformer_encoder (Transforme (None, None, 256)    3155456     positional_embedding[0][0]
__________________________________________________________________________________________________
model_1 (Functional)            (None, None, 15000)  12959640    decoder_inputs[0][0]
                                                                 transformer_encoder[0][0]
==================================================================================================
Total params: 19,960,216
Trainable params: 19,960,216
Non-trainable params: 0
__________________________________________________________________________________________________
1302/1302 [==============================] - 1297s 993ms/step - loss: 1.6495 - accuracy: 0.428

<tensorflow.python.keras.callbacks.History at 0x164a6c250>
```

Decoding test sentences

Finally, let's demonstrate how to translate brand new English sentences. We simply feed into the model the vectorized English sentence as well as the target token "[start]", then we repeatedly generated the next token, until we hit the token "[end]".

```
spa_vocab = spa_vectorization.get_vocabulary()
spa_index_lookup = dict(zip(range(len(spa_vocab)), spa_vocab))
max_decoded_sentence_length = 20


def decode_sequence(input_sentence):
    tokenized_input_sentence = eng_vectorization([input_sentence])
    decoded_sentence = "[start]"
    for i in range(max_decoded_sentence_length):
        tokenized_target_sentence = spa_vectorization([decoded_sentence])[:, :-1]
        predictions = transformer([tokenized_input_sentence, tokenized_target_sentence])

        sampled_token_index = np.argmax(predictions[0, i, :])
        sampled_token = spa_index_lookup[sampled_token_index]
        decoded_sentence += " " + sampled_token

        if sampled_token == "[end]":
            break
    return decoded_sentence


test_eng_texts = [pair[0] for pair in test_pairs]
for _ in range(30):
    input_sentence = random.choice(test_eng_texts)
    translated = decode_sequence(input_sentence)
```

<u>After 30 epochs, we get results such as:</u>

1. She handed him the money. [start] ella le pasó el dinero [end]
2. Tom has never heard Mary sing. [start] tom nunca ha oído cantar a mary [end]
3. Perhaps she will come tomorrow. [start] tal vez ella vendrá mañana [end]
4. I love to write. [start] me encanta escribir [end]
5. His French is improving little by little. [start] su francés va a [UNK] sólo un poco [end]
6. My hotel told me to call you. [start] mi hotel me dijo que te [UNK] [end]

Conclusion:

Language Translation is definitely the most required feature a person can ask, The reason being that when we move from place to place we encounter many different languages.

To communicate we need to learn the particular language of that reason, so with code provided we can reduce the efforts of learning new languages.

References:

The dataset is taken from internet   -----→   English-to-Spanish translation dataset provided by Anki (It has the languages English and Spanish)

The code featured here in the report is adapted from the book Deep Learning with Python, Second Edition (chapter 11: Deep learning for text).