Language Translation- English to French.

Seq2Seq is a method of encoder-decoder based machine translation and language processing that maps an input of sequence to an output of sequence with a tag and attention value.

In this file, we'll be training a sequence to sequence model on a dataset of English and French sentences that can translate new sentences from English to French.

The Data

Since translating the whole language of English to French will take lots of time to train, I'm making use of a small portion of the English corpus.

```
In [1]:
```

```
import helper
import problem_unittests as tests

#getting the data
source_path = 'data/small_vocab_en'
target_path = 'data/small_vocab_fr'
source_text = helper.load_data(source_path)
target_text = helper.load_data(target_path)
```

Exploring the Data:-

```
In [2]:
view sentence range = (2000, 2010)
import numpy as np
print('Dataset Stats')
print('Roughly the number of unique words: {}'.format(len({word: None for word in source
text.split() })))
#splitting
sentences = source text.split('\n')
word counts = [len(sentence.split()) for sentence in sentences]
print('Number of sentences: {}'.format(len(sentences)))
print('Average number of words in a sentence: {}'.format(np.average(word_counts)))
print()
print('English sentences {} to {}:'.format(*view sentence range))
print('\n'.join(source text.split('\n')[view sentence range[0]:view sentence range[1]]))
print('French sentences {} to {}:'.format(*view sentence range))
print('\n'.join(target_text.split('\n')[view_sentence_range[0]:view_sentence_range[1]]))
Dataset Stats
Roughly the number of unique words: 227
Number of sentences: 137861
Average number of words in a sentence: 13.225277634719028
English sentences 2000 to 2010:
she saw the shiny red automobile .
new jersey is pleasant during july , and it is sometimes freezing in april .
the peach is your most loved fruit , but the lemon is our most loved {\boldsymbol .}
he likes grapes , strawberries , and oranges.
```

new jersey is usually cold during november , but it is never warm in october .

```
the peach is her least favorite fruit , but the grapefruit is my least favorite .
china is never pleasant during spring , and it is usually dry in july .
california is never dry during fall , but it is never wonderful in autumn .
how was your visit to china last autumn ?
china is sometimes chilly during may , but it is sometimes cold in spring .
French sentences 2000 to 2010:
elle a vu la brillante voiture rouge .
new jersey est agréable en juillet , et il est parfois le gel en avril .
la pêche est votre fruit le plus aimé , mais le citron est notre plus aimé .
il aime les raisins , les fraises et les oranges .
new jersey est généralement froid en novembre , mais il est jamais chaud en octobre .
la pêche est moins son fruit préféré , mais le pamplemousse est mon préféré moins .
chine est jamais agréable au printemps , et il est généralement sec en juillet .
californie est jamais à sec pendant l' automne , mais il est jamais merveilleux à l' auto
comment était votre visite en chine l'automne dernier ?
la chine est parfois frisquet en mai , mais il est parfois froid au printemps .
```

Preprocessing Function:-

Text to Word Ids

We'll now turn the text into a number to make our computer understand it. In the function $text_to_ids()$, we will turn source_text and target_text from words to ids. However, you need to add the <EOS> word id at the end of each sentence from $target_text$. This particular thing will help the neural network predict when the sentence should end.

Creating a function named "text_to_ids" which will fulfil our purpose.

```
In [3]:
```

```
def text to ids(source text, target_text, source_vocab_to_int, target_vocab_to_int):
#converting source and target text to proper word ids
   source_sentences = source_text.split('\n')
   target sentences = target text.split('\n')
   source_id_text = []
   target_id_text = []
   for sentence in source sentences:
       source sentence id text = []
       for word in sentence.split():
            source sentence id text.append(source vocab to int[word])
       source id text.append(source sentence id text)
   for sentence in target sentences:
       target sentence id text = []
       for word in sentence.split():
            target sentence id text.append(target vocab to int[word])
        target sentence id text.append(target vocab to int['<EOS>'])
        target_id_text.append(target sentence id text)
   return source_id_text, target_id_text
tests.test_text_to_ids(text_to_ids)
```

Tests Passed

helper.preprocess_and_save_data(source_path, target_path, text_to_ids)

Building the Neural Network- The following are necessary to build a Sequence-to-Sequence model:-

process_decoding_input, encoding_layer, decoding_layer_train, decoding_layer_infer, decoding_layer, seq2seq_model

Function 'model_inputs' will return a tuple holding input, targets, learning rate, keep probability.

```
In [7]:
```

```
def model_inputs():
    inputs = tf.placeholder(tf.int32, [None, None], name="input")
    targets = tf.placeholder(tf.int32, [None, None])
    learning_rate = tf.placeholder(tf.float32)
    keep_prob = tf.placeholder(tf.float32, name="keep_prob")
    return inputs, targets, learning_rate, keep_prob

tests.test_model_inputs(model_inputs)
```

Tests Passed

Process Decoding Input

Implement process_decoding_input using TensorFlow to remove the last word id from each batch in target data and concat the GO ID to the begining of each batch.

```
In [8]:
```

```
def process_decoding_input(target_data, target_vocab_to_int, batch_size):
    ending = tf.strided_slice(target_data, [0, 0], [batch_size, -1], [1, 1])
    decoded_input = tf.concat([tf.fill([batch_size, 1], target_vocab_to_int['<GO>']), en
ding], 1)
    return decoded_input
tests.test_process_decoding_input(process_decoding_input)
```

Tests Passed

Encoding

Implement encoding_layer() to create a Encoder RNN layer using [tf.nn.dynamic_rnn()]

Here, param rnn_inputs= Inputs for the RNN, param rnn_size= RNN Size, param num_layers= Number of layers, param keep_prob= Dropout keep probability

```
In [9]:
```

```
def encoding_layer(rnn_inputs, rnn_size, num_layers, keep_prob):

   LSTM_cell = tf.contrib.rnn.BasicLSTMCell(rnn_size)
   LSTM_cell = tf.contrib.rnn.DropoutWrapper(LSTM_cell, keep_prob)
   encoded_cell = tf.contrib.rnn.MultiRNNCell([LSTM_cell] * num_layers)

   _, RNN_state = tf.nn.dynamic_rnn(encoded_cell, rnn_inputs, dtype=tf.float32)
```

```
return RNN_state

tests.test_encoding_layer(encoding_layer)
```

Tests Passed

Decoding - Training

Create training logits using tf.contrib.seq2seq.dynamic_rnn_decoder() . Apply the output_fn to the tf.contrib.seq2seq.dynamic_rnn_decoder() outputs.

```
In [10]:
```

Tests Passed

Decoding - Inference

Create inference logits using tf.contrib.seq2seq.simple_decoder_fn_inference() and tf.contrib.seq2seq.dynamic rnn decoder().

```
In [11]:
```

Tests Passed

Build the Decoding Layer

Implementing the function decoding layer () to create a Decoder RNN layer.

- Create RNN cell for decoding using rnn size and num layers.
- A Create the output funtion using [lambda] to transform it is input logite to class logite

```
In [12]:
```

```
def decoding layer(dec embed input, dec embeddings, encoder state, vocab size, sequence l
ength, rnn size,
                   num layers, target vocab to int, keep prob):
    # Creating RNN cell for decoding using rnn size and num layers
    dec cell = tf.contrib.rnn.MultiRNNCell([tf.contrib.rnn.BasicLSTMCell(rnn size)] * nu
m layers)
    # Create output function using lambda to transform inputs, logits, to class logits
    with tf.variable_scope("decoding") as decoding scope:
        output fn = lambda x: tf.contrib.layers.fully connected(x, vocab size, None, sco
pe=decoding scope)
    # Use decoding layer train() function to get training logits
    with tf.variable scope("decoding") as decoding scope:
        training logits = decoding layer train(
            encoder state, dec cell, dec embed input, sequence length, decoding scope, o
utput fn, keep prob)
    # Use decoding layer infer() function to get inference logits
    with tf.variable scope("decoding", reuse=True) as decoding scope:
       inference logits = decoding layer infer(
            encoder state, dec cell, dec embeddings, target vocab to int['<GO>'], target
_vocab_to int['<EOS>'],
           sequence length - 1, vocab size, decoding scope, output fn, keep prob)
    return training logits, inference logits
tests.test decoding layer(decoding layer)
```

Tests Passed

Build the Neural Network

Now we will be applying the functions implemented above to and combine the model:-

```
In [13]:
```

```
def seq2seq model(input data, target data, keep prob, batch size, sequence length, source
_vocab_size, target_vocab_size,
                  enc embedding size, dec embedding size, rnn size, num layers, target v
ocab_to_int):
    # Apply embedding to input data
    enc embed input = tf.contrib.layers.embed_sequence(input_data, source_vocab_size, en
c embedding size)
    # Encode the input using the encoding layer() function.
    encoder state = encoding layer(enc embed input, rnn size, num layers, keep prob)
    # Process target data using process decoding input() function.
    decoded_input = process_decoding_input(target_data, target vocab to int, batch size)
    # Apply embedding to target data for the decoder.
    dec embeddings = tf.Variable(tf.random uniform([target vocab size, dec embedding siz
e]))
    dec embed input = tf.nn.embedding lookup(dec embeddings, decoded input)
    # Decode the encoded input using decoding layer() function.
    training logits, inference_logits = decoding_layer(
        dec_embed_input, dec_embeddings, encoder_state, target_vocab_size, sequence_leng
th,
        rnn size, num layers, target vocab to int, keep prob)
    return training logits, inference logits
```

```
tests.test_seq2seq_model(seq2seq_model)
```

Tests Passed

Neural Network Training

Defining all the hyperparameters:-

```
In [40]:
```

```
epochs = 30

batch_size = 256

rnn_size = 100

num_layers = 2

# Embedding Size
encoding_embedding_size = 100
decoding_embedding_size = 100
learning_rate = 0.001
# Dropout Keep Probability
keep_probability = 0.9
```

Build the Graph

Build the graph using the neural network you implemented.

```
In [41]:
```

```
save path = 'checkpoints/dev'
(source int text, target int text), (source vocab to int, target vocab to int), = help
er.load preprocess()
max source sentence length = max([len(sentence) for sentence in source int text])
train_graph = tf.Graph()
with train graph.as default():
   input data, targets, lr, keep prob = model inputs()
    sequence length = tf.placeholder with default(max source sentence length, None, name
='sequence length')
   input shape = tf.shape(input data)
    train logits, inference logits = seg2seg model(
       tf.reverse(input data, [-1]), targets, keep prob, batch size, sequence length, 1
en(source vocab to int), len(target vocab to int),
       encoding embedding size, decoding embedding size, rnn size, num layers, target vo
cab to int)
    tf.identity(inference logits, 'logits')
    with tf.name scope("optimization"):
        # Loss function
       cost = tf.contrib.seq2seq.sequence loss(
            train logits,
            targets,
           tf.ones([input_shape[0], sequence_length]))
        # Optimizer
       optimizer = tf.train.AdamOptimizer(lr)
        # Gradient Clipping
       gradients = optimizer.compute gradients(cost)
       capped gradients = [(tf.clip by value(grad, -1., 1.), var) for grad, var in grad
ients if grad is not None]
       train op = optimizer.apply gradients(capped gradients)
```

Training the NN on the preprocessed data

```
In [42]:
import time
def get accuracy(target, logits):
    max seq = max(target.shape[1], logits.shape[1])
    if max seq - target.shape[1]:
        target = np.pad(
            target,
            [(0,0),(0,max_seq - target.shape[1])],
            'constant')
    if max seq - logits.shape[1]:
        logits = np.pad(
            logits,
            [(0,0),(0,\max \text{ seq - logits.shape}[1]),(0,0)],
            'constant')
    return np.mean(np.equal(target, np.argmax(logits, 2)))
train source = source int text[batch size:]
train target = target int text[batch size:]
valid source = helper.pad sentence batch(source int text[:batch size])
valid target = helper.pad sentence batch(target int text[:batch size])
with tf.Session(graph=train graph) as sess:
    sess.run(tf.global variables initializer())
    for epoch i in range(epochs):
        for batch i, (source batch, target batch) in enumerate(
                helper.batch data(train source, train target, batch size)):
            start_time = time.time()
            _, loss = sess.run(
                [train op, cost],
                {input data: source batch,
                 targets: target batch,
                 lr: learning rate,
                 sequence length: target batch.shape[1],
                 keep prob: keep probability})
            batch train logits = sess.run(
                inference logits,
                {input data: source batch, keep prob: 1.0})
            batch valid logits = sess.run(
                inference logits,
                {input_data: valid_source, keep_prob: 1.0})
            train acc = get accuracy(target batch, batch train logits)
            valid acc = get accuracy(np.array(valid_target), batch_valid_logits)
            end time = time.time()
        print('Epoch {:>3} Batch {:>4}/{} - Train Accuracy: {:>6.3f}, Validation Accurac
y: {:>6.3f}, Loss: {:>6.3f}'
              .format(epoch i, batch i, len(source int text) // batch size, train acc, v
alid acc, loss))
    # Save Model
    saver = tf.train.Saver()
    saver.save(sess, save path)
    print('Model Trained and Saved')
Epoch
        0 Batch 536/538 - Train Accuracy: 0.529, Validation Accuracy: 0.553, Loss: 1.
020
Epoch
       1 Batch 536/538 - Train Accuracy: 0.626, Validation Accuracy: 0.639, Loss:
605
       2 Batch 536/538 - Train Accuracy: 0.772, Validation Accuracy: 0.741, Loss: 0.
Epoch
380
```

```
Epoch
        3 Batch
                  536/538 - Train Accuracy:
                                              0.863, Validation Accuracy:
                                                                             0.840, Loss:
                                                                                            0.
224
Epoch
        4 Batch
                  536/538 - Train Accuracy:
                                              0.901, Validation Accuracy:
                                                                             0.881, Loss:
                                                                                            0.
127
        5 Batch
                  536/538 - Train Accuracy:
                                              0.921, Validation Accuracy:
                                                                             0.906, Loss:
                                                                                            0.
Epoch
086
                  536/538 - Train Accuracy:
                                                                             0.929, Loss:
        6 Batch
                                              0.931, Validation Accuracy:
                                                                                            0.
Epoch
066
Epoch
        7 Batch
                  536/538 - Train Accuracy:
                                              0.943, Validation Accuracy:
                                                                             0.929, Loss:
                                                                                            0.
054
Epoch
        8 Batch
                  536/538 - Train Accuracy:
                                              0.949, Validation Accuracy:
                                                                             0.941, Loss:
                                                                                            0.
043
Epoch
        9 Batch
                  536/538 - Train Accuracy:
                                              0.956, Validation Accuracy:
                                                                             0.947, Loss:
                                                                                            0.
037
                  536/538 - Train Accuracy:
Epoch
       10 Batch
                                              0.959, Validation Accuracy:
                                                                             0.953, Loss:
                                                                                            0 .
032
                                              0.957, Validation Accuracy:
Epoch
       11 Batch
                  536/538 - Train Accuracy:
                                                                             0.946, Loss:
                                                                                            0.
027
       12 Batch
                  536/538 - Train Accuracy:
                                              0.962, Validation Accuracy:
                                                                             0.946, Loss:
                                                                                            0.
Epoch
024
Epoch
       13 Batch
                  536/538 - Train Accuracy:
                                              0.964, Validation Accuracy:
                                                                             0.948, Loss:
                                                                                            0.
022
                  536/538 - Train Accuracy:
                                              0.965, Validation Accuracy:
                                                                             0.955, Loss:
       14 Batch
                                                                                            0.
Epoch
020
                  536/538 - Train Accuracy:
                                                                             0.953, Loss:
       15 Batch
                                              0.971, Validation Accuracy:
                                                                                            0.
Epoch
017
                                              0.971, Validation Accuracy:
                  536/538 - Train Accuracy:
                                                                             0.947, Loss:
Epoch
       16 Batch
                                                                                            0.
016
Epoch
       17 Batch
                  536/538 - Train Accuracy:
                                              0.974, Validation Accuracy:
                                                                             0.958, Loss:
                                                                                            0.
016
       18 Batch
                  536/538 - Train Accuracy:
                                              0.969, Validation Accuracy:
                                                                             0.959, Loss:
                                                                                            0.
Epoch
014
                                                                             0.961, Loss:
                  536/538 - Train Accuracy:
                                              0.967, Validation Accuracy:
                                                                                            0.
       19 Batch
Epoch
013
Epoch
       20 Batch
                  536/538 - Train Accuracy:
                                              0.974, Validation Accuracy:
                                                                             0.965, Loss:
                                                                                            0.
012
       21 Batch
                  536/538 - Train Accuracy:
                                              0.975, Validation Accuracy:
                                                                             0.966, Loss:
                                                                                            0.
Epoch
011
Epoch
       22 Batch
                  536/538 - Train Accuracy:
                                              0.977, Validation Accuracy:
                                                                             0.966, Loss:
                                                                                            0.
010
                  536/538 - Train Accuracy:
                                              0.975, Validation Accuracy:
                                                                             0.965, Loss:
Epoch
       23 Batch
                                                                                            0.
010
       24 Batch
                  536/538 - Train Accuracy:
                                              0.975, Validation Accuracy:
                                                                             0.963, Loss:
                                                                                            0.
Epoch
011
                  536/538 - Train Accuracy:
                                              0.972, Validation Accuracy:
                                                                             0.973, Loss:
Epoch
       25 Batch
                                                                                            0.
010
       26 Batch
                  536/538 - Train Accuracy:
                                              0.977, Validation Accuracy:
                                                                             0.966, Loss:
Epoch
                                                                                            0.
008
                  536/538 - Train Accuracy:
Epoch
       27 Batch
                                              0.976, Validation Accuracy:
                                                                             0.968, Loss:
                                                                                            0.
009
       28 Batch
                  536/538 - Train Accuracy:
                                              0.978, Validation Accuracy:
                                                                             0.959, Loss:
Epoch
                                                                                            0.
009
       29 Batch 536/538 - Train Accuracy:
Epoch
                                              0.975, Validation Accuracy:
                                                                             0.965, Loss:
                                                                                            0.
009
Model Trained and Saved
```

Save Parameters

Save the batch size and save path parameters for inference.

In [43]:

```
# Save parameters for checkpoint
helper.save params(save path)
```

Sentence to Sequence

To feed a sentence into the model for translation, you first need to preprocess it. Implement the function

sentence to seq() to preprocess new sentences.

- Convert the sentence to lowercase
- Convert words into ids using vocab_to_int
 - Convert words not in the vocabulary, to the <UNK> word id.

```
In [45]:
```

```
def sentence_to_seq(sentence, vocab_to_int):

    # Convert sentence to lowercase.
    sentence_l = sentence.lower()

# Convert words to ids using vocab_to_int.
    word_ids = []
    for word in sentence_l.split():
        if word in vocab_to_int.keys():
            word_ids.append(vocab_to_int[word])
        else:
            word_ids.append(vocab_to_int['<UNK>'])

    return word_ids

tests.test_sentence_to_seq(sentence_to_seq)
```

Tests Passed

Translate

This will translate translate sentence from English to French.

```
In [51]:
```

```
translate sentence = 'france is lovely in the spring .'
late sentence = sentence to seq(translate sentence, source vocab to int)
loaded graph = tf.Graph()
with tf.Session(graph=loaded graph) as sess:
   # Load saved model
    loader = tf.train.import meta graph(load path + '.meta')
   loader.restore(sess, load path)
    input data = loaded graph.get tensor by name('input:0')
    logits = loaded graph.get tensor by name('logits:0')
    keep prob = loaded graph.get tensor by name('keep prob:0')
    translate logits = sess.run(logits, {input data: [translate sentence], keep prob: 1.
0})[0]
print('Input')
print(' Word Ids:
                    {}'.format([i for i in translate sentence]))
print(' English Words: {}'.format([source int to vocab[i] for i in translate sentence])
print('\nPrediction')
print(' Word Ids:
                       {}'.format([i for i in np.argmax(translate logits, 1)]))
print(' French Words: {}'.format([target_int_to_vocab[i] for i in np.argmax(translate_l
ogits, 1)]))
Input
              [175, 134, 2, 174, 146, 116, 56]
 English Words: ['france', 'is', '<UNK>', 'in', 'the', 'spring', '.']
Prediction
                [333, 157, 121, 335, 297, 141, 179, 110, 1]
 French Words: ['la', 'france', 'est', 'jamais', 'sec', 'au', 'printemps', '.', '<EOS>']
```