Language_Modeling

April 15, 2020

STAY SAFE !!

HW4 Language Modeling (LM)

Due: April 2020 10th, 23:59

In this homework, you will first implement a simple bigram language model on a dataset containing news headlines, learn basic concepts of marcov modeling, words sampling, and perplexity.

Then things start get very fun and open ended. You will be shown a simple word based RNN LM. Understand how it works, and then apply changes to it as you wish. Things you can try but not limited to:

1. Word based RNN model with subword embedding
2. Character based RNN model
3. Try different model architecture
4. Try different training corprus
5. Personalized LM

You are given the following files: - `Language_Modeling.ipynb`: Notebook file with starter code - `headlines.train`: Training set to train your model - `headlines.dev`: Test set to report your model's performance - `glove_300d.csv`: Glove embedding truncated for the vocab in the training data - `../utils/`: folder containing all utility code for the series of homeworks

Deriverables: - pdf or html of the notebook - A report of your own model if you have

0.0.1 ========================== Coding starts here ======================

1 Setup

1.1 Load functions

```
In [3]: %load_ext autoreload
        %autoreload 2
        %matplotlib inline
        import os, sys, random
        import pandas as pd
        import numpy as np
        from nltk.stem import WordNetLemmatizer
        from nltk import word_tokenize

        # add utils folder to path
        p = os.path.dirname(os.getcwd())
```

```
    if p not in sys.path:
        sys.path = [p] + sys.path

from utils.hw4 import (load_data, load_data_char, gen_vocab, START, END, UNK,
                       load_embedding)
from utils.general import sigmoid, tanh, show_keras_model
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

1.2 Load data

```
In [4]: # The input is trucated for fast iteration
        # Remember to use the full set of data for your final model training
        # It may take some time
        headlines_train = load_data("headlines.train")
        headlines_dev = load_data("headlines.dev")

        # Before we begin, let's look at what some of the headlines look like.
        # Run the following code block as many times as you want to get a sense
        # of what kind of headlines we hope to generate.
        for headline in random.sample(headlines_train, 5):
            print(START + ' '.join(headline) + END)
```

```
<START>the dogleg january 17<END>
<START>england in command in second test<END>
<START>hicks political issues all used up dad<END>
<START>pms quiet diplomacy on china under fire<END>
<START>media merger wont change wagga ownership<END>
```

```
In [5]: # Calculate the vocab list and the embedding
        # It (might) be helpful to remove low frequency words, so the model learns how to
        # treat unseen vocabulary
        vocab, re_vocab = gen_vocab(headlines_train, 4)
        sent_len = max([len(s) for s in headlines_train]) + 1

        print("Size of vocab: ", len(vocab))
        print("Longest setence length: ", sent_len)

        # Load the embedding, trick is played to fill the missing vocab
        # you can look into the source file to see what it actually does
        # This embedding file is truncated for vocab used in this dataset
        # If you are to train your own model with your own data, remember to download
        # the original embedding here: https://nlp.stanford.edu/projects/glove/
        glove = load_embedding('glove_300d.csv', vocab=vocab)

        glove.T.head()
```

```
Size of vocab:  19366
Longest setence length:  15
```

```
[5]:        <UNK>   <START>     <END>         to         in      for         of  \
     0 -0.577407  0.054423  0.499353 -0.248370  0.068507 -0.23909 -0.036429
     1  0.716811 -0.174687 -1.011034 -0.454610 -0.023344 -0.64189 -0.285920
     2  0.188384 -0.237130 -0.282649  0.039227  0.282710 -0.58322  0.063387
     3 -0.035630 -0.070880 -0.226818 -0.284220 -0.402150 -0.54743 -0.601220
     4  0.594462 -0.032176  0.346658 -0.031852  0.077815  0.42386 -0.015309
```

```
         on      over       the   …    doctoring      udia    aircon  \
0  0.000607 -0.089285 -0.208380   …    -0.402415 -0.016445 -0.518557
1  0.048631 -0.077838 -0.149320   …     0.075237  0.015756 -0.958881
2  0.489690 -0.295420 -0.017528   …    -0.075572 -0.006419 -1.081884
3  0.427770 -0.335840 -0.028432   …     0.010410 -0.010890  1.092362
4 -0.386100  0.287430 -0.060104   …    -0.663541  0.002630  0.493826

       kent   squalor  pilkadaris        jb        tc    troupe    hotham
0  0.298390  0.176240    0.506266  0.490685  0.051306 -1.019067  0.748168
1 -0.137968 -0.132954    0.794788 -0.146615 -0.140802 -0.210929 -1.215811
2 -0.300228  0.134589   -0.379868  0.445029 -0.039547 -0.554600 -1.260959
3  0.441796 -0.321358    0.059644 -0.352571 -0.071938 -0.981091 -1.207408
4 -0.030233 -0.425027    0.116036 -0.465117 -0.182486  0.647981  0.438689

[5 rows x 19366 columns]
```

```
In [6]: # Transform the DF to np array
        glove = glove.values
```

1.3 Util function

```
In [7]: def to_label(token):
            """
            Simply transfer a token to its numerical label, if the token is not int
            the vocab, return the label of UNK
            input:
                token: str

            output:
                int
            """
            return re_vocab.get(token, re_vocab[UNK])

        def to_embedding(X):
            """
            For the 2 dimensional input X filled with the vocabulary label,
            return an np.array of their embedding

            input:
                X: np.array(n_sample, sent_len)

            return:
                embdding
            """
            embedding = np.zeros((len(X), len(X[0]), glove.shape[1]))

            for i in range(len(X)):
                for j in range(len(X[0])):
                    embedding[i,j,:] = glove[X[i][j]]

            return embedding

        def sample_with_weight(prob, avoid_UNK=True):
            """
            For a given probability distribution, return a random int sampled by the
            probability distribution.

            input:
                prob: list of float probability
        avoid_UNK: boolean, if UNK should be excluded
    """
    unk_idx = re_vocab[UNK]

    if avoid_UNK:
        prob[unk_idx] = 0 # Make sure we do not use UNK in the generated text

    # If the distribution is 0, use uniform distribution
    if prob.sum() <= 0:
        prob[1:] = 1.0

    return np.random.choice(range(len(prob)), p=prob/prob.sum())
```

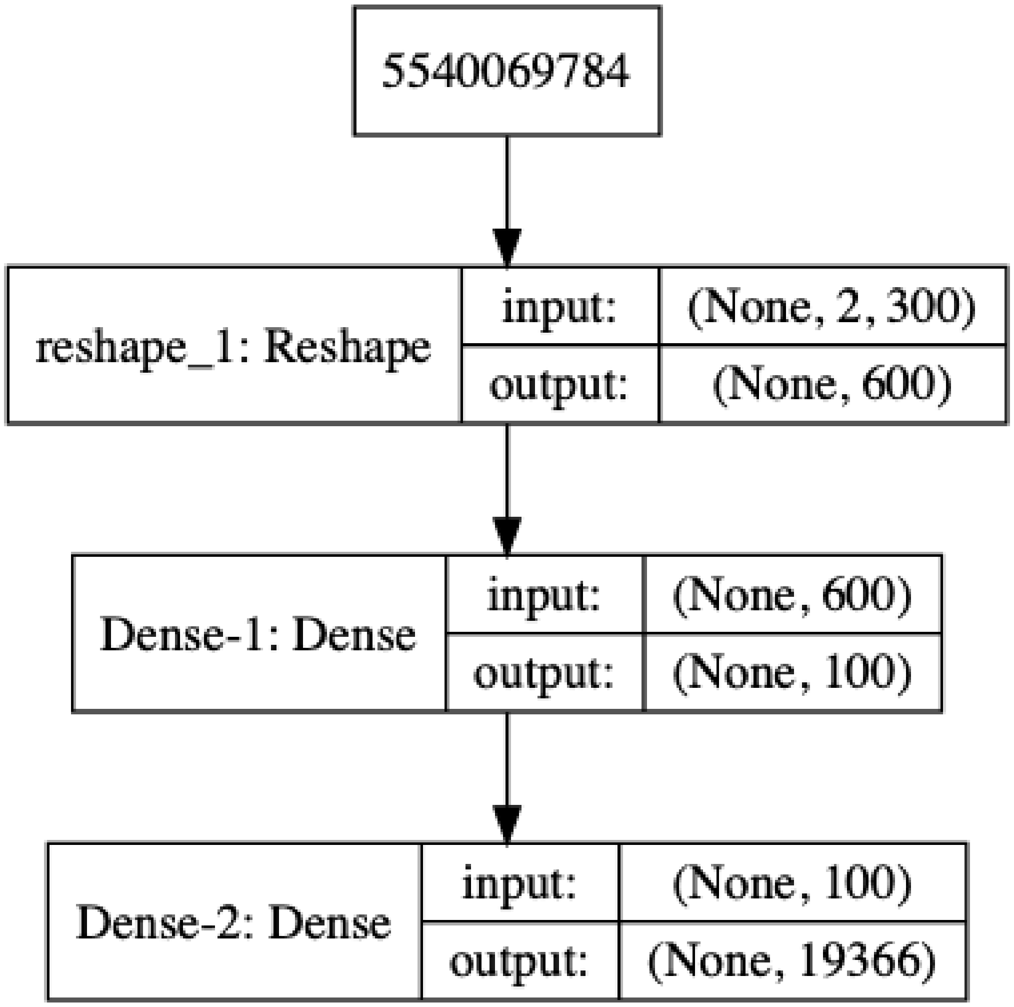
2 Tri-gram (second order) Markov Model

2.1 Build FNN Bi-Gram model

In [8]:
```
from keras.models import Sequential
from keras.layers import Dense, Reshape

n_gram = 2

# For simplicity, we use the embedding of words to feed the model, therefore
# no need to add a Embedding layer in the begining. But for a possibly better
performance
# you can add a embedding layer, even better if you use the glove embedding matrix as
the
# initial value for the embedding layer
# This is useful also because we have filled the embedding with random values for those
missing
# vocabularies, allowing the embedding matrix to relax during training will improve the
performance
# for these words as well. But be prepared that this would slow down the training
FNN_model = Sequential()
FNN_model.add(Reshape(target_shape=(n_gram * glove.shape[1],),
                      input_shape=(n_gram, glove.shape[1],)))
FNN_model.add(Dense(100, activation="relu", name="Dense-1"))
FNN_model.add(Dense(len(vocab), activation="softmax", name="Dense-2"))

FNN_model.summary()
show_keras_model(FNN_model)
```

```
WARNING: Logging before flag parsing goes to stderr.
W0411 22:05:35.925065 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:74: The
name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph
instead.

W0411 22:05:35.962076 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:517: The
name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0411 22:05:35.993237 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:4138: The
name tf.random_uniform is deprecated. Please use tf.random.uniform instead.



_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
reshape_1 (Reshape)          (None, 600)               0
_________________________________________________________________
Dense-1 (Dense)              (None, 100)               60100
_________________________________________________________________
Dense-2 (Dense)              (None, 19366)             1955966
=================================================================
Total params: 2,016,066
Trainable params: 2,016,066
Non-trainable params: 0
_________________________________________________________________
```

[8]:



2.2 Training data generator

```
In [9]: from keras.utils import to_categorical
        import random

        def gen_sample_FNN(data, batch_size=1000, one_hot=True):
            """
        For training the model, we need to shift the data by -1 to produce
        label, i.g.
        ["word1", "word2", "word3", "word4"] -->
        X: [[START, STSRT],
            [START, 1],
            [1, 2],
            [2, 3],
            [3, 4]]
        Y: [1, 2, 3, 4, ...] if one_hot is False, the label is translated to
            one-hot if ont_hot is True

        inputs:
            data: list of list of strings
            batch_size: int
            one_hot: boolean

        outputs:
            X: np.array(batch_size, n_gram, embedding_dim)
            Y: np.array(batch_size, ) or np.array(batch_size, vocab_size)

        batch size is used to control the size for each data batch
        set batch_size = -1 if you don't want to generate by batch
        """
        if batch_size == -1:
            batch_size = sum([len(s) + 1 for s in data])

        while True:
            # Use shuffle so the order in each epoch is different
            random.shuffle(data)

            X, Y = [], []
            for d in data:
                encodes = [re_vocab[START], re_vocab[START]] +\
                          [to_label(t) for t in d] +\
                          [re_vocab[END]]
                for i in range(len(encodes) - 2):
                    X.append([encodes[i], encodes[i+1]])
                    Y.append(encodes[i+2])

                    if len(X) >= batch_size:
                        X = to_embedding(X)
                        Y = np.array(Y)

                        if one_hot:
                            Y = to_categorical(Y, num_classes=len(re_vocab))

                        yield X, Y
                        X, Y = [], []
```

2.3 Generate text

```
In [10]: def generate_text_FNN(model, max_len=sent_len-1, seed=None):
             """
             For a given FNN model, generate text. If seed is not provided,
             use START as initial seed.

             inputs:
                 model: FNN model
                 max_len: int, maximum length of the setence
                 seed: str, the seed word used to generate the text
             """

             result = []
             prev = START
             if not seed:
                 seed = START # <START> <START>  // <START> seed
```

```
        result.append(seed)
        next_word = None
        while len(result) < max_len and next_word != END:
            input_X = [[to_label(prev),to_label(seed)]]
            input_X = to_embedding(input_X)
            prob = model.predict(input_X).flatten()
            sample = sample_with_weight(prob)
            next_word = vocab[sample]
            result.append(next_word)
            prev, seed = seed, next_word

        """
        hints:
        1. It's a trigram model, what your intial seed look like?
        2. The prediction of each state should return a list of probability, use the
           `sample_with_weight` function to help you sample the next word.
        3. When the word END is sampled, you need to stop the setence. Also use the max_len
           to force ending the setence to avoid the program running forever.
        """

        return ' '.join(result)
```

```
In [11]: # Before we train the model, let first check if the text generation function
         # works as expected. Don't worry if the sentence doesn't make any sense.
         # We haven't trained the model yet!
         generate_text_FNN(FNN_model, seed="china")
```

```
W0411 22:05:41.307667 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:2741: The
name tf.Session is deprecated. Please use tf.compat.v1.Session instead.

W0411 22:05:41.310365 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:174: The
name tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session
instead.
```

```
[11]: 'china ipcc bella distribution refutes institution caleb von shotgun wasting
      masterchef accounting rather dealings'
```

2.4 Calculate Perplexity

```
In [12]: def calculate_perplexity_FNN(model, X, y):
             """
             For a given FNN model, and test data, calcualte the perplexity.
             The definition of perplexity is:

             perplexity = exp(- \sum_i log(P_i) / N)

             inputs:
                 model: FNN model
                 X: np.array(n_sample, n_gram, embedding_dim)
                 y: np.array(n_sample), int label of the next word
             """

             prob = model.predict(X)
             P = 0.
             N = len(y)
             for s in range(N):
                 P += np.log(prob[s,y[s]])

             perplexity = np.exp(-P/N)
```

```
    """

    hits:
        1. First make the prod prediction using the model
        2. The probability at the position of y is what you look for

    When you have too much UNK word, you will find the perplexity to be lower, but it
doesn't
    really mean your model is better, can you think why?
    """

    return perplexity
```

When we have too much UNK word in the dev set, that means the dev set has many words that is not in the training set vocabulary, When y_i is UNKNOWN P_i would be large, then perplexity is small. The preplexity only reflects the goodness of prediction when most of the words are using the save vocab and does not have many UNKNOWNS.

if the model predict a lot of UNK words. he UNK word will process a very high probabality while the other tokens have lower probablities. The labels are meaningful words so the P_i will be a very small positive number, then the perplexity is also going to be unreasonable small.

if the model just predict random probablitities, then:

$p_i = \frac{1}{vocab\_size}$

$\sum_i log(P_i)/N = -N * \frac{log(vocab\_size)}{N} = -log(vocab\_size)$

$perplexity = exp(-\sum_i log(P_i)/N) = vocab\_size$

In [13]:
```
# Let check the perplexity for the untrained model
# Is your value close to the number of vocabulary?
# Is this a coincidence?
X_dev_FNN, y_dev_FNN = next(gen_sample_FNN(headlines_dev, batch_size=-1, one_hot=False))

calculate_perplexity_FNN(FNN_model, X_dev_FNN, y_dev_FNN)
```

[13]:
```
19379.232239654484
```

2.5 Training the model

In [14]:
```
"""
Let's use the function defined above to report the model performance
after each epoch
"""
def on_epoch_end_FNN(epoch, logs):
    print('----- Generating text after Epoch: %d' % epoch)
    for i in range(3):
        print(generate_text_FNN(FNN_model))
    print('Current perplexity on dev data: ',
          calculate_perplexity_FNN(FNN_model, X_dev_FNN, y_dev_FNN), '\n')
```

In [15]:
```
from keras.callbacks import LambdaCallback

"""
Notice how the metrics / generated text evolve after each epoch
"""
FNN_model.compile(loss='categorical_crossentropy',
             optimizer='adam',
             metrics=['accuracy', 'top_k_categorical_accuracy'])

batch_size = 512
steps_per_epoch = sum([len(s) + 1 for s in headlines_train]) // batch_size + 1
FNN_model.fit_generator(gen_sample_FNN(headlines_train, batch_size=batch_size),
                        epochs = 10, steps_per_epoch=steps_per_epoch,
                        callbacks=[LambdaCallback(on_epoch_end=on_epoch_end_FNN)])
```

```
W0411 22:06:00.654759 4525321664 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/optimizers.py:790: The name
tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0411 22:06:00.847187 4525321664 deprecation.py:323] From
/usr/local/lib/python3.6/site-packages/tensorflow/python/ops/math_grad.py:1250:
add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where


Epoch 1/10
  39/2892 […] - ETA: 13:21 - loss: 8.9232 - acc: 0.1096 -
top_k_categorical_accuracy: 0.1897
```

```
        ␣
 ↪---------------------------------------------------------------------------

        KeyboardInterrupt                         Traceback (most recent call␣
 ↪last)

        <ipython-input-15-cc9d5461a3e8> in <module>
         12 FNN_model.fit_generator(gen_sample_FNN(headlines_train,␣
 ↪batch_size=batch_size),
         13                         epochs = 10, steps_per_epoch=steps_per_epoch,
    ---> 14                         ␣
 ↪callbacks=[LambdaCallback(on_epoch_end=on_epoch_end_FNN)])


        /usr/local/lib/python3.6/site-packages/keras/legacy/interfaces.py in␣
 ↪wrapper(*args, **kwargs)
         89                 warnings.warn('Update your `' + object_name + '`␣
 ↪call to the ' +
         90                               'Keras 2 API: ' + signature,␣
 ↪stacklevel=2)
    ---> 91             return func(*args, **kwargs)
         92         wrapper._original_function = func
         93         return wrapper
```

```
      /usr/local/lib/python3.6/site-packages/keras/engine/training.py in␣
↪fit_generator(self, generator, steps_per_epoch, epochs, verbose, callbacks,␣
↪validation_data, validation_steps, class_weight, max_queue_size, workers,␣
↪use_multiprocessing, shuffle, initial_epoch)
     1416                 use_multiprocessing=use_multiprocessing,
     1417                 shuffle=shuffle,
  -> 1418                 initial_epoch=initial_epoch)
     1419 
     1420     @interfaces.legacy_generator_methods_support


      /usr/local/lib/python3.6/site-packages/keras/engine/training_generator.
↪py in fit_generator(model, generator, steps_per_epoch, epochs, verbose,␣
↪callbacks, validation_data, validation_steps, class_weight, max_queue_size,␣
↪workers, use_multiprocessing, shuffle, initial_epoch)
      215                     outs = model.train_on_batch(x, y,
      216                                                            ␣
↪sample_weight=sample_weight,
  --> 217                                                            ␣
↪class_weight=class_weight)
      218 
      219                     outs = to_list(outs)


      /usr/local/lib/python3.6/site-packages/keras/engine/training.py in␣
↪train_on_batch(self, x, y, sample_weight, class_weight)
     1215                 ins = x + y + sample_weights
     1216             self._make_train_function()
  -> 1217             outputs = self.train_function(ins)
     1218             return unpack_singleton(outputs)
     1219 


      /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.
↪py in __call__(self, inputs)
     2713                     return self._legacy_call(inputs)
     2714 
  -> 2715                 return self._call(inputs)
     2716             else:
     2717                 if py_any(is_tensor(x) for x in inputs):


      /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.
↪py in _call(self, inputs)
     2673                 fetched = self._callable_fn(*array_vals,␣
↪run_metadata=self.run_metadata)
     2674             else:
```

```
    -> 2675             fetched = self._callable_fn(*array_vals)
       2676         return fetched[:len(self.outputs)]
       2677


        /usr/local/lib/python3.6/site-packages/tensorflow/python/client/session.
↪py in __call__(self, *args, **kwargs)
       1456         ret = tf_session.TF_SessionRunCallable(self._session.
↪_session,
       1457                                                self._handle, args,
    -> 1458                                                run_metadata_ptr)
       1459         if run_metadata:
       1460           proto_data = tf_session.TF_GetBuffer(run_metadata_ptr)


        KeyboardInterrupt:
```

3 Word-based RNN Language Model

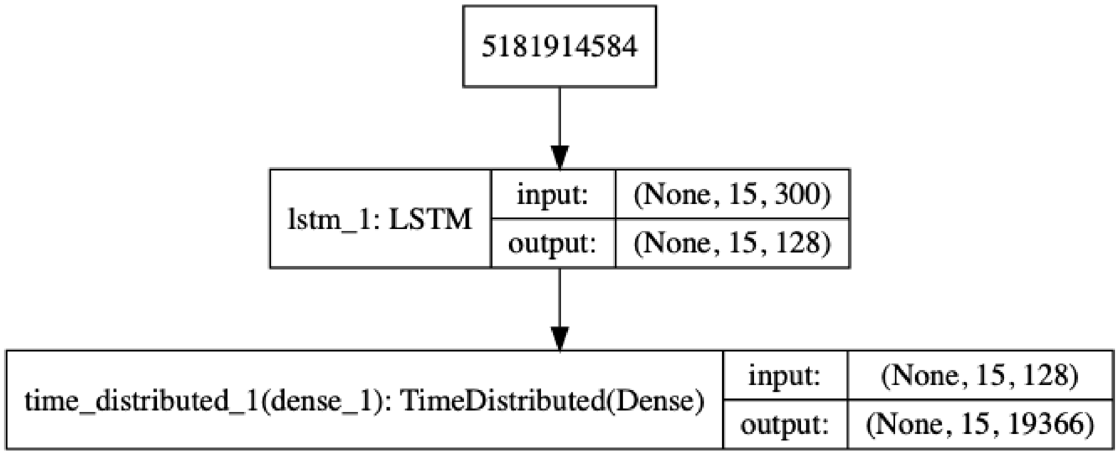
3.1 Build LSTM model

```
In [16]: from keras.layers import Dense, LSTM, Activation, TimeDistributed

         # For simplicity, we use the embedding of words to feed the model, therefore
         # no need to add a Embedding layer in the begining. But for a possibly better
         performance
         # you can add a embedding layer, even better if you use the glove embedding matrix as
         the
         # initial value for the embedding layer
         # This is useful also because we have filled the embedding with random values for those
         missing
         # vocabularies, allowing the embedding matrix to relax during training will improve the
         performance
         # for these words as well. But be prepared that this would slow down the training

         # Unfortunately Keras does not have an easy way to support dynamic length of input for
         RNN model.
         # So we use the sent_len to truncate all the sentences.
         batch_size = 10
         RNN_train_model = Sequential()
         RNN_train_model.add(
             LSTM(128, input_shape=(sent_len, glove.shape[1]), return_sequences=True)
             )
         RNN_train_model.add(TimeDistributed(Dense(len(vocab), activation='softmax')))
         RNN_train_model.summary()
         show_keras_model(RNN_train_model)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 15, 128)           219648
_________________________________________________________________
time_distributed_1 (TimeDist (None, 15, 19366)         2498214
=================================================================
Total params: 2,717,862
```

```
Trainable params: 2,717,862
Non-trainable params: 0
_________________________________________________________________
```

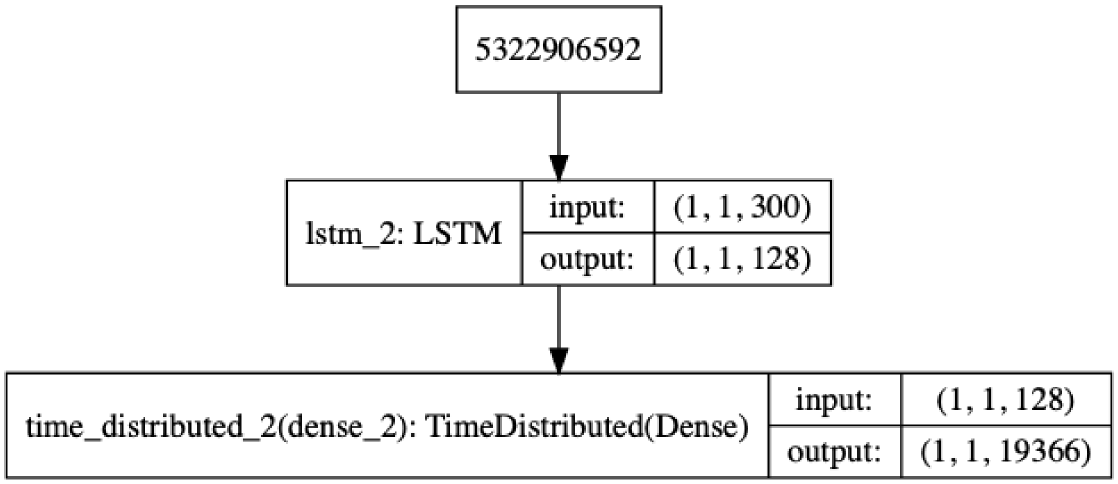
[16]:



```
In [17]: from keras.layers import Dense, LSTM, Activation, TimeDistributed

         """
         # It's tricky to explain why we need the RNN_pred_model.
         # The RNN_train_model.predict requires a fix length of input (sent_len in our case).
         # This is not convenient for us because we need to generate the next text one by one.
         # The trick we play here is to create a shadow model having only 1 time step. We will
         # copy the parameter of the RNN_train_model to this model once it's trained.
         # Check generate_text_RNN function to understand details, and there is some discussion
         # here: "https://github.com/keras-team/keras/issues/8771"
         """

         RNN_pred_model = Sequential()
         RNN_pred_model.add(
             LSTM(128, batch_input_shape=(1, 1, glove.shape[1]), return_sequences=True, stateful
         = True)
             )
         RNN_pred_model.add(TimeDistributed(Dense(len(vocab), activation='softmax')))
         RNN_pred_model.summary()
         show_keras_model(RNN_pred_model)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_2 (LSTM)                (1, 1, 128)               219648
_________________________________________________________________
time_distributed_2 (TimeDist (1, 1, 19366)             2498214
=================================================================
Total params: 2,717,862
Trainable params: 2,717,862
Non-trainable params: 0
_________________________________________________________________
```

[17]:



3.2 Training data generator

```
In [18]: from keras.preprocessing.sequence import pad_sequences

         def gen_sample_RNN(data, batch_size=100, one_hot=True):
             """
             The input is the same to the FNN model, but the output training data is different.

             inputs:
                 data: list of list of string
                 batch_size: int
                 one_hot: boolean

             output:
                 X: np.array(batch_size, sent_len, embedding_dim)
                 Y: np.array(batch_size, sent_len, ) or np.array(batch_size, sent_len,
         vocab_size)
             """
             if batch_size == -1:
                 batch_size = len(data)

             while True:
                 # Shuffle the data so data order is different for different epochs
                 random.shuffle(data)

                 X, Y = [], []
                 for s in data:
                     X.append([to_label(START)] + [to_label(t) for t in s])
                     Y.append([to_label(t) for t in s] + [to_label(END)])

                     if len(X) >= batch_size:
                         X = pad_sequences(sequences=X, maxlen=sent_len, padding='post',
         value=to_label(END))
                         Y = pad_sequences(sequences=Y, maxlen=sent_len, padding='post',
         value=to_label(END))

                         if one_hot: Y = to_categorical(Y, num_classes=len(re_vocab))

                         yield to_embedding(X), Y

                         X, Y = [], []
```

3.3 Generate text

```
In [19]: def generate_text_RNN(model, max_len=sent_len-1, seed=None):
             """
             Use the RNN_pred_model to generate text. Notice how we use the stateful model to
         generate
             the next word one by one. Make sure you fully understand each line of this code.
             """
             if seed is None:
                 seed = START
                 result = []
             else:
                 result = [seed]

             model.reset_states()

             for i in range(max_len):
                 X = to_embedding([[to_label(seed)]])
                 idx = sample_with_weight(model.predict(X)[0][0])

                 if vocab[idx] == END: break

                 seed = vocab[idx]
                 result.append(seed)

             return ' '.join(result)
```

```
In [20]: generate_text_RNN(RNN_pred_model, seed="china")
```

```
[20]: 'china madoff nasty dividend immune playboy supercomputer monaro battens
      davydenko outer resourced rev shower who'
```

3.4 Calculate Perplexity

```
In [21]: def calculate_perplexity_RNN(model, X, y):
             """
             For a given FNN model, and test data, calcualte the perplexity.
             The definition of perplexity is:

             perplexity = exp(- \sum_i log(P_i) / N)

             inputs:
                 model: FNN model
                 X: np.array(n_sample, sent_len, embedding_dim)
                 y: np.array(n_sample, sent_len), int labels
             """
             prob = model.predict(X)
             M = 0
             P = 0
             N, sent_len = y.shape
             for s in range(N):
                 for l in range(sent_len):
                     if y[s,l] == re_vocab[END]:
                         break
                     P += np.log(prob[s,l,y[s,l]])
                     M += 1

             perplexity = np.exp(-P/M)
             """

             hits:
                 1. First make the prod prediction using the RNN_train_model
                 2. The probability at the position of y is what you look for
                 3. All sentences have fixed length, meaning a sentence can have multiple padding
```

```
END at the end
            of a sentence. Consider stop counting the perplexity once you hit the first
END, otherwise
            your perplexity will seem too good.

    When you have too much UNK word, you will find the perplexity to be lower, but it
doesn't
    really mean your model is better, can you think why?
    """

    return perplexity
```

In [22]:
```
# Let check the perplexity for the untrained model
# Is your value close to the number of vocabulary?
# Is this a coincidence?
X_dev_RNN, y_dev_RNN = next(gen_sample_RNN(headlines_dev, batch_size=-1, one_hot=False))

calculate_perplexity_RNN(RNN_train_model, X_dev_RNN, y_dev_RNN)
```

[22]:
```
19389.0952061517
```

3.5 Train model

In [23]:
```
"""
Let's use the function defined above to report the model performance
after each epoch
"""
def on_epoch_end_RNN(epoch, logs):
    RNN_pred_model.set_weights(RNN_train_model.get_weights())
    print('----- Generating text after Epoch: %d' % epoch)
    for i in range(3):
        print(generate_text_RNN(RNN_pred_model))
    print('Current perplexity on dev data: ',
          calculate_perplexity_RNN(RNN_train_model, X_dev_RNN, y_dev_RNN), '\n')
```

In [24]:
```
"""
Notice how the metrics / generated text evolve after each epoch
"""
batch_size = 10
num_batches = len(headlines_train) // batch_size
RNN_train_model.compile(loss='categorical_crossentropy', optimizer='adam')
RNN_train_model.fit_generator(gen_sample_RNN(headlines_train, batch_size), num_batches,
10,
          callbacks=[LambdaCallback(on_epoch_end=on_epoch_end_RNN)])
```

```
Epoch 1/10
20000/20000 [==============================] - 2069s 103ms/step - loss: 3.1110
----- Generating text after Epoch: 0
fairfax pulls aim to 100 million from f
adams west farmers association council questions
q history peninsula for historic
Current perplexity on dev data:  839.0277186026706

Epoch 2/10
20000/20000 [==============================] - 2270s 114ms/step - loss: 2.8319
----- Generating text after Epoch: 1
hospital patients held to save survey
abc sport
cricket x palau mottram to custody over game ticket medal
Current perplexity on dev data:  727.8745405344695

Epoch 3/10
20000/20000 [==============================] - 2911s 146ms/step - loss: 2.7508
```

```
----- Generating text after Epoch: 2
rolf harris named worlds most british mcdonalds show
suspects return home may wounds
philip devastated by wall street
Current perplexity on dev data:  725.0630279119446

Epoch 4/10
20000/20000 [==============================] - 3231s 162ms/step - loss: 2.7050
----- Generating text after Epoch: 3
tenders search for pool tasmanian patients eased
beat books with handed over laws
dispute over sa bikie links with city mother
Current perplexity on dev data:  730.8918182273915

Epoch 5/10
20000/20000 [==============================] - 2476s 124ms/step - loss: 2.6775
----- Generating text after Epoch: 4
simplot stays the far
conroy leads landmark job
bail at overboard home from exhibition thief
Current perplexity on dev data:  741.7261396177381

Epoch 6/10
20000/20000 [==============================] - 1940s 97ms/step - loss: 2.6604
----- Generating text after Epoch: 5
group urges probe into northern listed
river water buyback and fundraising says leading freight
taskforce delivers road spirit message
Current perplexity on dev data:  755.8500756955898

Epoch 7/10
20000/20000 [==============================] - 1906s 95ms/step - loss: 2.6473
----- Generating text after Epoch: 6
water corp profits rise
all stars win power plant release
investigation puts bushfire planners told
Current perplexity on dev data:  753.0262128720698

Epoch 8/10
20000/20000 [==============================] - 1952s 98ms/step - loss: 2.6372
----- Generating text after Epoch: 7
nasa chief defends issues of canberra unrest
passengers indemnity safety breaches
gillard accuses nationals vote for federal budget debate
Current perplexity on dev data:  753.738548188292

Epoch 9/10
20000/20000 [==============================] - 1913s 96ms/step - loss: 2.6284
----- Generating text after Epoch: 8
childs people need to protect youth information
libya groups unhappy as political comeback
mp backs coal industry predicts consumer news looms
Current perplexity on dev data:  762.0487302550855

Epoch 10/10
20000/20000 [==============================] - 1933s 97ms/step - loss: 2.6210
----- Generating text after Epoch: 9
priest stock poisoning of missing mans body
consumers to be about wind farm in turn a chronic
```

```
amazon board member fails to widen galaxy deaths
Current perplexity on dev data:  753.098036491844
```

```
[24]: <keras.callbacks.History at 0x13bf43be0>
```

```
In [ ]:
```