In [1]:
```
import os
os.environ['CUDA_VISIBLE_DEVICES'] = '0'
```

Artificial Intelligence Nanodegree

Voice User Interfaces

Project: Speech Recognition with Neural Networks

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following blocks of code will require additional functionality which you must provide. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to \n",

```
"**File -> Download as -> HTML (.html)**. Include the
finished document along with this notebook as your
submission.
```

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.

Introduction

In this notebook, you will build a deep neural network that functions as part of an end-to-end automatic speech recognition (ASR) pipeline! Your completed pipeline will accept raw audio as input and return a predicted transcription of the spoken language. The full pipeline is summarized in the figure below.

- **STEP 1** is a pre-processing step that converts raw audio to one of two feature representations that are commonly used for ASR.
- **STEP 2** is an acoustic model which accepts audio features as input and returns a probability distribution over all potential transcriptions. After learning about the basic types of neural networks that are often used for acoustic modeling, you will engage in your own investigations, to design your own acoustic model!
- **STEP 3** in the pipeline takes the output from the acoustic model and returns a predicted transcription.

Feel free to use the links below to navigate the notebook:

The Data

We begin by investigating the dataset that will be used to train and evaluate your pipeline. LibriSpeech is a large corpus of English-read speech, designed for training and evaluating models for ASR. The dataset contains 1000 hours of speech derived from audiobooks. We will work with a small subset in this project, since larger-scale data would take a long while to train. However, after completing this project, if you are interested in exploring further, you are encouraged to work with more of the data that is provided online.

In the code cells below, you will use the `vis_train_features` module to visualize a training example. The supplied argument `index=0` tells the module to extract the first example in the training set. (You are welcome to change `index=0` to point to a different training example, if you like, but please **DO NOT** amend any other code in the cell.) The returned variables are:

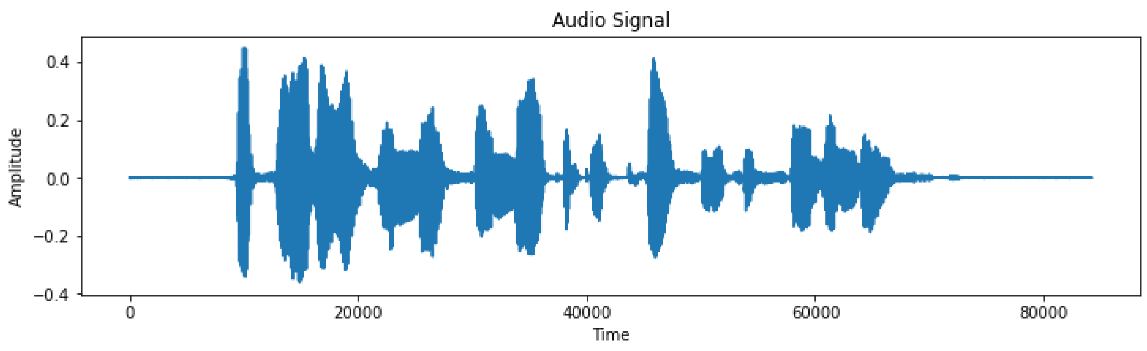
- `vis_text` - transcribed text (label) for the training example.
- `vis_raw_audio` - raw audio waveform for the training example.
- `vis_mfcc_feature` - mel-frequency cepstral coefficients (MFCCs) for the training example.
- `vis_spectrogram_feature` - spectrogram for the training example.
- `vis_audio_path` - the file path to the training example.

In [2]:
```
from data_generator import vis_train_features

# extract label and audio features for a single training example
vis_text, vis_raw_audio, vis_mfcc_feature, vis_spectrogram_feature, vis_a
```

```
There are 2023 total training examples.
```

The following code cell visualizes the audio waveform for your chosen example, along with the corresponding transcript. You also have the option to play the audio in the notebook!

In [3]:
```
from IPython.display import Markdown, display
from data_generator import vis_train_features, plot_raw_audio
from IPython.display import Audio
%matplotlib inline

# plot audio signal
plot_raw_audio(vis_raw_audio)
# print length of audio signal
display(Markdown('**Shape of Audio Signal** : ' + str(vis_raw_audio.shape
# print transcript corresponding to audio clip
display(Markdown('**Transcript** : ' + str(vis_text)))
# play the audio file
Audio(vis_audio_path)
```



Shape of Audio Signal : (84231,)

Transcript : her father is a most remarkable person to say the least

Out[3]:

STEP 1: Acoustic Features for Speech Recognition

For this project, you won't use the raw audio waveform as input to your model. Instead, we provide code that first performs a pre-processing step to convert the raw audio to a feature representation that has historically proven successful for ASR models. Your acoustic model will accept the feature representation as input.

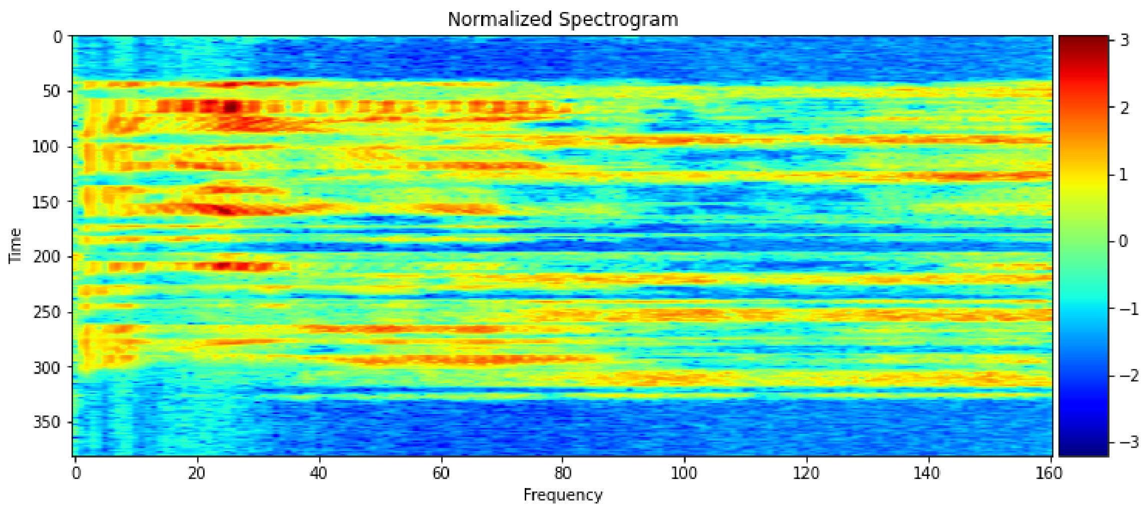
In this project, you will explore two possible feature representations. *After completing the project*, if you'd like to read more about deep learning architectures that can accept raw audio input, you are encouraged to explore this research paper.

Spectrograms

The first option for an audio feature representation is the spectrogram. In order to complete this project, you will **not** need to dig deeply into the details of how a spectrogram is calculated; but, if you are curious, the code for calculating the spectrogram was borrowed from this repository. The implementation appears in the `utils.py` file in your repository.

The code that we give you returns the spectrogram as a 2D tensor, where the first (*vertical*) dimension indexes time, and the second (*horizontal*) dimension indexes frequency. To speed the convergence of your algorithm, we have also normalized the spectrogram. (You can see this quickly in the visualization below by noting that the mean value hovers around zero, and most entries in the tensor assume values close to zero.)

```
In [4]: from data_generator import plot_spectrogram_feature

        # plot normalized spectrogram
        plot_spectrogram_feature(vis_spectrogram_feature)
        # print shape of spectrogram
        display(Markdown('**Shape of Spectrogram** : ' + str(vis_spectrogram_feat
```



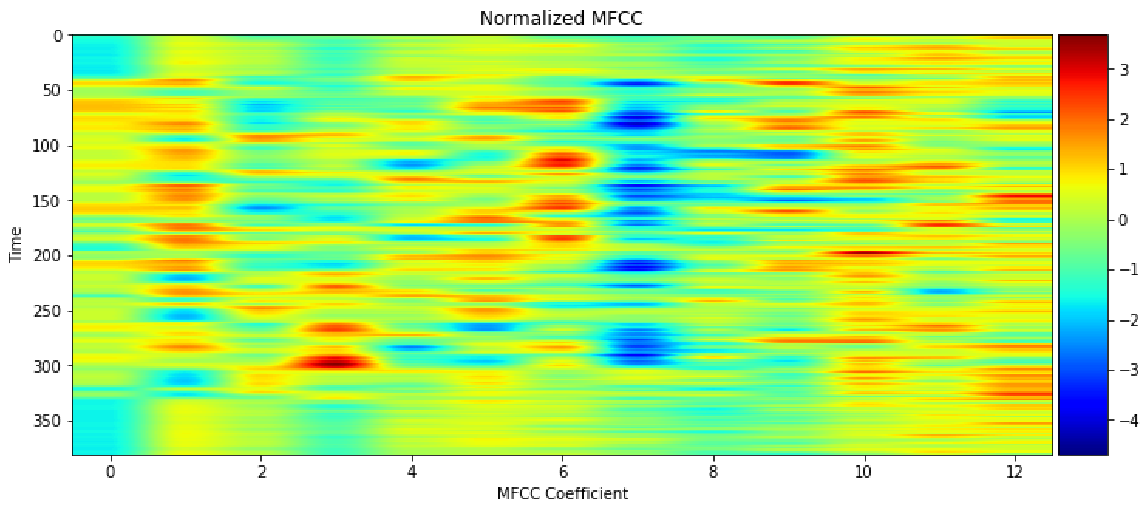
Shape of Spectrogram : (381, 161)

Mel-Frequency Cepstral Coefficients (MFCCs)

The second option for an audio feature representation is MFCCs. You do **not** need to dig deeply into the details of how MFCCs are calculated, but if you would like more information, you are welcome to peruse the documentation of the `python_speech_features` Python package. Just as with the spectrogram features, the MFCCs are normalized in the supplied code.

The main idea behind MFCC features is the same as spectrogram features: at each time window, the MFCC feature yields a feature vector that characterizes the sound within the window. Note that the MFCC feature is much lower-dimensional than the spectrogram feature, which could help an acoustic model to avoid overfitting to the training dataset.

In [5]:
```
from data_generator import plot_mfcc_feature

# plot normalized MFCC
plot_mfcc_feature(vis_mfcc_feature)
# print shape of MFCC
display(Markdown('**Shape of MFCC** : ' + str(vis_mfcc_feature.shape)))
```



Shape of MFCC : (381, 13)

When you construct your pipeline, you will be able to choose to use either spectrogram or MFCC features. If you would like to see different implementations that make use of MFCCs and/or spectrograms, please check out the links below:

- This repository uses spectrograms.
- This repository uses MFCCs.
- This repository also uses MFCCs.
- This repository experiments with raw audio, spectrograms, and MFCCs as features.

STEP 2: Deep Neural Networks for Acoustic Modeling

In this section, you will experiment with various neural network architectures for acoustic modeling.

You will begin by training five relatively simple architectures. **Model 0** is provided for you. You will write code to implement **Models 1**, **2**, **3**, and **4**. If you would like to experiment further, you are welcome to create and train more models under the **Models 5+** heading.

All models will be specified in the `sample_models.py` file. After importing the `sample_models` module, you will train your architectures in the notebook.

After experimenting with the five simple architectures, you will have the opportunity to compare their performance. Based on your findings, you will construct a deeper architecture that is designed to outperform all of the shallow models.

For your convenience, we have designed the notebook so that each model can be specified and trained on separate occasions. That is, say you decide to take a break from the notebook after training **Model 1**. Then, you need not re-execute all prior code cells in the notebook before training **Model 2**. You need only re-execute the code cell below, that is marked with **`RUN THIS CODE CELL IF YOU ARE RESUMING THE NOTEBOOK AFTER A BREAK`**, before transitioning to the code cells corresponding to **Model 2**.

In [1]:
```
#######################################################################
# RUN THIS CODE CELL IF YOU ARE RESUMING THE NOTEBOOK AFTER A BREAK #
#######################################################################

# allocate 50% of GPU memory (if you like, feel free to change this)
from keras.backend.tensorflow_backend import set_session
import tensorflow as tf
config = tf.ConfigProto()
config.gpu_options.per_process_gpu_memory_fraction = 0.5
set_session(tf.Session(config=config))

# watch for any changes in the sample_models module, and reload it automa
%load_ext autoreload
%autoreload 2
# import NN architectures for speech recognition
from sample_models import *
# import function for training acoustic model
from train_utils import train_model
```

```
WARNING:tensorflow:Deprecation warnings have been disabled. Set TF_ENABL
E_DEPRECATION_WARNINGS=1 to re-enable them.
```

```
Using TensorFlow backend.
```

Model 0: RNN

Given their effectiveness in modeling sequential data, the first acoustic model you will use is an RNN. As shown in the figure below, the RNN we supply to you will take the time sequence of audio features as input.

At each time step, the speaker pronounces one of 28 possible characters, including each of the 26 letters in the English alphabet, along with a space character (" "), and an apostrophe (').

The output of the RNN at each time step is a vector of probabilities with 29 entries, where the $i$-th entry encodes the probability that the $i$-th character is spoken in the time sequence. (The extra 29th character is an empty "character" used to pad training examples within batches containing uneven lengths.) If you would like to peek under the hood at how characters are mapped to indices in the probability vector, look at the `char_map.py` file in the repository. The figure below shows an equivalent, rolled depiction of the RNN that shows the output layer in greater detail.

The model has already been specified for you in Keras. To import it, you need only run the code cell below.

In [7]:
```
model_0 = simple_rnn_model(input_dim=161) # change to 13 if you would lik
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:508: The name tf.placeholder is deprecated. P
lease use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:68: The name tf.get_default_graph is deprecat
ed. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3837: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.

_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
rnn (GRU)                    (None, None, 29)          16617     
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 16,617
Trainable params: 16,617
Non-trainable params: 0
_________________________________________________________________
None
```

As explored in the lesson, you will train the acoustic model with the CTC loss criterion. Custom loss functions take a bit of hacking in Keras, and so we have implemented the CTC loss function for you, so that you can focus on trying out as many deep learning architectures as possible :). If you'd like to peek at the implementation details, look at the `add_ctc_loss` function within the `train_utils.py` file in the repository.

To train your architecture, you will use the `train_model` function within the `train_utils` module; it has already been imported in one of the above code cells. The `train_model` function takes three **required** arguments:

- `input_to_softmax` - a Keras model instance.
- `pickle_path` - the name of the pickle file where the loss history will be saved.
- `save_model_path` - the name of the HDF5 file where the model will be saved.

If we have already supplied values for `input_to_softmax`, `pickle_path`, and `save_model_path`, please **DO NOT** modify these values.

There are several **optional** arguments that allow you to have more control over the training process. You are welcome to, but not required to, supply your own values for these arguments.

- `minibatch_size` - the size of the minibatches that are generated while training the model (default: `20`).
- `spectrogram` - Boolean value dictating whether spectrogram (`True`) or MFCC (`False`) features are used for training (default: `True`).
- `mfcc_dim` - the size of the feature dimension to use when generating MFCC features (default: `13`).
- `optimizer` - the Keras optimizer used to train the model (default: `SGD(lr=0.02, decay=1e-6, momentum=0.9, nesterov=True, clipnorm=5)`).
- `epochs` - the number of epochs to use to train the model (default: `20`). If you choose to modify this parameter, make sure that it is *at least* 20.
- `verbose` - controls the verbosity of the training output in the `model.fit_generator` method (default: `1`).
- `sort_by_duration` - Boolean value dictating whether the training and validation sets are sorted by (increasing) duration before the start of the first epoch (default: `False`).

The `train_model` function defaults to using spectrogram features; if you choose to use these features, note that the acoustic model in `simple_rnn_model` should have `input_dim=161`. Otherwise, if you choose to use MFCC features, the acoustic model should have `input_dim=13`.

We have chosen to use `GRU` units in the supplied RNN. If you would like to experiment with `LSTM` or `SimpleRNN` cells, feel free to do so here. If you change the `GRU` units to `SimpleRNN` cells in `simple_rnn_model`, you may notice that the loss quickly becomes undefined (`nan`) - you are strongly encouraged to check this for yourself! This is due to the exploding gradients problem. We have already implemented gradient clipping in your optimizer to help you avoid this issue.

IMPORTANT NOTE: If you notice that your gradient has exploded in any of the models below, feel free to explore more with gradient clipping (the `clipnorm` argument in your optimizer) or swap out any `SimpleRNN` cells for `LSTM` or `GRU` cells. You can also try restarting the kernel to restart the training process.

In [8]:

```
train_model(input_to_softmax=model_0,
            pickle_path='model_0.pickle',
            save_model_path='model_0.h5',
            spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3952: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:757: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:977: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:964: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:168: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:184: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:193: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:200: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 101s 998ms/step - loss: 852.9
660 - val_loss: 757.5558
Epoch 2/20
101/101 [==============================] - 101s 1s/step - loss: 779.4397
- val_loss: 761.6699
Epoch 3/20
101/101 [==============================] - 102s 1s/step - loss: 777.9938
- val_loss: 757.3842
Epoch 4/20
101/101 [==============================] - 102s 1s/step - loss: 778.5655
- val_loss: 753.2747
Epoch 5/20
101/101 [==============================] - 101s 1s/step - loss: 777.2697
- val_loss: 759.3686
Epoch 6/20
101/101 [==============================] - 101s 1s/step - loss: 778.2557
- val_loss: 753.4225
Epoch 7/20
101/101 [==============================] - 102s 1s/step - loss: 777.9566
- val_loss: 760.3146
Epoch 8/20
101/101 [==============================] - 101s 1s/step - loss: 778.0940
- val_loss: 757.5974
Epoch 9/20
```

```
101/101 [==============================] - 101s 1s/step - loss: 777.8943
- val_loss: 753.5028
Epoch 10/20
101/101 [==============================] - 101s 997ms/step - loss: 777.1
462 - val_loss: 757.9185
Epoch 11/20
101/101 [==============================] - 101s 1000ms/step - loss: 777.
5004 - val_loss: 754.6709
Epoch 12/20
101/101 [==============================] - 101s 1s/step - loss: 778.0108
- val_loss: 759.6416
Epoch 13/20
101/101 [==============================] - 101s 1s/step - loss: 777.5231
- val_loss: 755.8973
Epoch 14/20
101/101 [==============================] - 103s 1s/step - loss: 778.1245
- val_loss: 753.8410
Epoch 15/20
101/101 [==============================] - 101s 1s/step - loss: 778.0996
- val_loss: 748.6742
Epoch 16/20
101/101 [==============================] - 102s 1s/step - loss: 777.0277
- val_loss: 753.8970
Epoch 17/20
101/101 [==============================] - 101s 1s/step - loss: 777.4492
- val_loss: 756.9101
Epoch 18/20
101/101 [==============================] - 100s 993ms/step - loss: 777.5
411 - val_loss: 749.8924
Epoch 19/20
101/101 [==============================] - 102s 1s/step - loss: 777.3247
- val_loss: 756.4204
Epoch 20/20
101/101 [==============================] - 101s 1s/step - loss: 778.0573
- val_loss: 758.4202
```

(IMPLEMENTATION) Model 1: RNN + TimeDistributed Dense

Read about the TimeDistributed wrapper and the BatchNormalization layer in the Keras documentation. For your next architecture, you will add batch normalization to the recurrent layer to reduce training times. The `TimeDistributed` layer will be used to find more complex patterns in the dataset. The unrolled snapshot of the architecture is depicted below.

The next figure shows an equivalent, rolled depiction of the RNN that shows the (`TimeDistrbuted`) dense and output layers in greater detail.

Use your research to complete the `rnn_model` function within the `sample_models.py` file. The function should specify an architecture that satisfies the following requirements:

- The first layer of the neural network should be an RNN (`SimpleRNN` , `LSTM` , or `GRU`) that takes the time sequence of audio features as input. We have added `GRU` units for you, but feel free to change `GRU` to `SimpleRNN` or `LSTM` , if you like!
- Whereas the architecture in `simple_rnn_model` treated the RNN output as the final layer of the model, you will use the output of your RNN as a hidden layer. Use `TimeDistributed` to apply a `Dense` layer to each of the time steps in the RNN output. Ensure that each `Dense` layer has `output_dim` units.

Use the code cell below to load your model into the `model_1` variable. Use a value for `input_dim` that matches your chosen audio features, and feel free to change the values for `units` and `activation` to tweak the behavior of your recurrent layer.

In [2]:
```
model_1 = rnn_model(input_dim=161, # change to 13 if you would like to us
                    units=200,
                    activation='relu')
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:508: The name tf.placeholder is deprecated. P
lease use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:68: The name tf.get_default_graph is deprecat
ed. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3837: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:127: The name tf.placeholder_with_default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.


_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
rnn (GRU)                    (None, None, 200)         217200    
_________________________________________________________________
bn_rnn_1d (BatchNormalizatio (None, None, 200)         800       
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 29)          5829      
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 223,829
Trainable params: 223,429
Non-trainable params: 400
_________________________________________________________________
None
```

Please execute the code cell below to train the neural network you specified in `input_to_softmax` . After the model has finished training, the model is saved in the HDF5 file `model_1.h5`. The loss history is saved in `model_1.pickle`. You are welcome to tweak any of the optional parameters while calling the `train_model` function, but this is not required.

In [3]:
```
train_model(input_to_softmax=model_1,
            pickle_path='model_1.pickle',
            save_model_path='model_1.h5',
            spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3952: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:757: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:977: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:964: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:168: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:184: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:193: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:200: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 103s 1s/step - loss: 301.3959
- val_loss: 234.6396
Epoch 2/20
101/101 [==============================] - 103s 1s/step - loss: 215.3389
- val_loss: 212.3043
Epoch 3/20
101/101 [==============================] - 103s 1s/step - loss: 190.3286
- val_loss: 183.2065
Epoch 4/20
101/101 [==============================] - 104s 1s/step - loss: 171.9545
- val_loss: 166.0209
Epoch 5/20
101/101 [==============================] - 103s 1s/step - loss: 160.5785
- val_loss: 163.2990
Epoch 6/20
101/101 [==============================] - 104s 1s/step - loss: 153.6530
- val_loss: 155.9617
Epoch 7/20
101/101 [==============================] - 103s 1s/step - loss: 147.6160
- val_loss: 152.7398
Epoch 8/20
101/101 [==============================] - 103s 1s/step - loss: 142.7623
- val_loss: 149.0897
Epoch 9/20
```

```
101/101 [==============================] - 104s 1s/step - loss: 138.9864
- val_loss: 147.5790
Epoch 10/20
101/101 [==============================] - 103s 1s/step - loss: 135.3479
- val_loss: 147.5971
Epoch 11/20
101/101 [==============================] - 104s 1s/step - loss: 132.9743
- val_loss: 144.3826
Epoch 12/20
101/101 [==============================] - 104s 1s/step - loss: 130.6857
- val_loss: 143.0201
Epoch 13/20
101/101 [==============================] - 103s 1s/step - loss: 128.1082
- val_loss: 146.3248
Epoch 14/20
101/101 [==============================] - 103s 1s/step - loss: 126.6580
- val_loss: 138.8765
Epoch 15/20
101/101 [==============================] - 105s 1s/step - loss: 125.6315
- val_loss: 143.2524
Epoch 16/20
101/101 [==============================] - 105s 1s/step - loss: 123.9744
- val_loss: 142.2260
Epoch 17/20
101/101 [==============================] - 104s 1s/step - loss: 122.8179
- val_loss: 139.2108
Epoch 18/20
101/101 [==============================] - 105s 1s/step - loss: 121.4680
- val_loss: 141.7481
Epoch 19/20
101/101 [==============================] - 104s 1s/step - loss: 122.3488
- val_loss: 140.3511
Epoch 20/20
101/101 [==============================] - 104s 1s/step - loss: 118.9630
- val_loss: 141.7228
```

(IMPLEMENTATION) Model 2: CNN + RNN + TimeDistributed Dense

The architecture in `cnn_rnn_model` adds an additional level of complexity, by introducing a 1D convolution layer.

This layer incorporates many arguments that can be (optionally) tuned when calling the `cnn_rnn_model` module. We provide sample starting parameters, which you might find useful if you choose to use spectrogram audio features.

If you instead want to use MFCC features, these arguments will have to be tuned. Note that the current architecture only supports values of `'same'` or `'valid'` for the `conv_border_mode` argument.

When tuning the parameters, be careful not to choose settings that make the convolutional layer overly small. If the temporal length of the CNN layer is shorter than the length of the transcribed text label, your code will throw an error.

Before running the code cell below, you must modify the `cnn_rnn_model` function in `sample_models.py`. Please add batch normalization to the recurrent layer, and provide the same `TimeDistributed` layer as before.

In [2]:
```
model_2 = cnn_rnn_model(input_dim=161, # change to 13 if you would like t
                        filters=200,
                        kernel_size=11,
                        conv_stride=2,
                        conv_border_mode='valid',
                        units=200)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:508: The name tf.placeholder is deprecated. P
lease use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3837: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:125: The name tf.get_default_graph is depreca
ted. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:127: The name tf.placeholder_with_default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.


_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
conv1d (Conv1D)              (None, None, 200)         354400    
_________________________________________________________________
bn_conv_1d (BatchNormalizati (None, None, 200)         800       
_________________________________________________________________
rnn (SimpleRNN)              (None, None, 200)         80200     
_________________________________________________________________
bn_rnn_1d (BatchNormalizatio (None, None, 200)         800       
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 29)          5829      
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 442,029
Trainable params: 441,229
Non-trainable params: 800
_________________________________________________________________
None
```

```
/usr/local/lib/python3.8/dist-packages/keras/layers/recurrent.py:989: Us
erWarning: The `implementation` argument in `SimpleRNN` has been depreca
ted. Please remove it from your layer call.
  warnings.warn('The `implementation` argument '
```

Please execute the code cell below to train the neural network you specified in `input_to_softmax`. After the model has finished training, the model is saved in the HDF5 file `model_2.h5`. The loss history is saved in `model_2.pickle`. You are welcome to tweak any of the optional parameters while calling the `train_model` function, but this is not required.

In [3]:
```
train_model(input_to_softmax=model_2,
            pickle_path='model_2.pickle',
            save_model_path='model_2.h5',
            spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3952: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:757: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:977: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:964: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:168: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:184: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:193: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:200: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 33s 323ms/step - loss: 243.89
51 - val_loss: 199.5135
Epoch 2/20
101/101 [==============================] - 26s 255ms/step - loss: 176.31
79 - val_loss: 163.2025
Epoch 3/20
101/101 [==============================] - 24s 240ms/step - loss: 152.95
28 - val_loss: 150.6068
Epoch 4/20
101/101 [==============================] - 24s 233ms/step - loss: 141.02
05 - val_loss: 147.0995
Epoch 5/20
101/101 [==============================] - 23s 232ms/step - loss: 132.69
81 - val_loss: 141.3714
Epoch 6/20
101/101 [==============================] - 23s 232ms/step - loss: 125.86
27 - val_loss: 138.6319
Epoch 7/20
101/101 [==============================] - 23s 229ms/step - loss: 120.73
00 - val_loss: 135.5060
Epoch 8/20
101/101 [==============================] - 23s 229ms/step - loss: 116.16
02 - val_loss: 136.3418
Epoch 9/20
```

```
101/101 [==============================] - 23s 227ms/step - loss: 111.90
14 - val_loss: 138.8069
Epoch 10/20
101/101 [==============================] - 23s 230ms/step - loss: 108.24
92 - val_loss: 137.1206
Epoch 11/20
101/101 [==============================] - 23s 226ms/step - loss: 104.93
73 - val_loss: 134.9496
Epoch 12/20
101/101 [==============================] - 23s 228ms/step - loss: 101.21
98 - val_loss: 135.0715
Epoch 13/20
101/101 [==============================] - 23s 227ms/step - loss: 98.318
5 - val_loss: 137.3323
Epoch 14/20
101/101 [==============================] - 23s 230ms/step - loss: 95.575
9 - val_loss: 138.2602
Epoch 15/20
101/101 [==============================] - 23s 227ms/step - loss: 93.007
1 - val_loss: 141.1420
Epoch 16/20
101/101 [==============================] - 23s 226ms/step - loss: 89.785
7 - val_loss: 139.2737
Epoch 17/20
101/101 [==============================] - 23s 228ms/step - loss: 87.396
3 - val_loss: 141.3206
Epoch 18/20
101/101 [==============================] - 23s 226ms/step - loss: 84.669
4 - val_loss: 141.8945
Epoch 19/20
101/101 [==============================] - 23s 226ms/step - loss: 82.446
3 - val_loss: 142.9868
Epoch 20/20
101/101 [==============================] - 23s 226ms/step - loss: 80.146
8 - val_loss: 149.2594
```

(IMPLEMENTATION) Model 3: Deeper RNN + TimeDistributed Dense

Review the code in `rnn_model`, which makes use of a single recurrent layer. Now, specify an architecture in `deep_rnn_model` that utilizes a variable number `recur_layers` of recurrent layers. The figure below shows the architecture that should be returned if `recur_layers=2`. In the figure, the output sequence of the first recurrent layer is used as input for the next recurrent layer.

Feel free to change the supplied values of `units` to whatever you think performs best. You can change the value of `recur_layers`, as long as your final value is greater than 1. (As a quick check that you have implemented the additional functionality in `deep_rnn_model` correctly, make sure that the architecture that you specify here is identical to `rnn_model` if `recur_layers=1`.)

In [4]:
```
model_3 = deep_rnn_model(input_dim=161, # change to 13 if you would like
                         units=200,
                              recur_layers=2)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:68: The name tf.get_default_graph is deprecat
ed. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3837: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:127: The name tf.placeholder_with_default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.


_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
rnn_0 (GRU)                  (None, None, 200)         217200    
_________________________________________________________________
bn_rnn_1d_0 (BatchNormalizat (None, None, 200)         800       
_________________________________________________________________
rnn_1 (GRU)                  (None, None, 200)         240600    
_________________________________________________________________
bn_rnn_1d_1 (BatchNormalizat (None, None, 200)         800       
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 29)          5829      
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 465,229
Trainable params: 464,429
Non-trainable params: 800
_________________________________________________________________
None
```

Please execute the code cell below to train the neural network you specified in `input_to_softmax`. After the model has finished training, the model is saved in the HDF5 file `model_3.h5`. The loss history is saved in `model_3.pickle`. You are welcome to tweak any of the optional parameters while calling the `train_model` function, but this is not required.

```
In [5]: train_model(input_to_softmax=model_3,
                    pickle_path='model_3.pickle',
                    save_model_path='model_3.h5',
                    spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3952: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:757: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:977: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:964: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:168: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:184: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:193: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:200: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 200s 2s/step - loss: 281.2890
- val_loss: 234.3806
Epoch 2/20
101/101 [==============================] - 202s 2s/step - loss: 220.0011
- val_loss: 209.7589
Epoch 3/20
101/101 [==============================] - 202s 2s/step - loss: 193.8483
- val_loss: 182.6410
Epoch 4/20
101/101 [==============================] - 201s 2s/step - loss: 168.2837
- val_loss: 165.4866
Epoch 5/20
101/101 [==============================] - 202s 2s/step - loss: 152.5801
- val_loss: 155.3851
Epoch 6/20
101/101 [==============================] - 201s 2s/step - loss: 142.0961
- val_loss: 143.9949
Epoch 7/20
101/101 [==============================] - 203s 2s/step - loss: 134.4138
- val_loss: 143.6280
Epoch 8/20
101/101 [==============================] - 202s 2s/step - loss: 128.5084
- val_loss: 139.0685
Epoch 9/20
```

```
101/101 [==============================] - 201s 2s/step - loss: 123.1011
- val_loss: 140.2469
Epoch 10/20
101/101 [==============================] - 201s 2s/step - loss: 118.6293
- val_loss: 133.7471
Epoch 11/20
101/101 [==============================] - 202s 2s/step - loss: 115.0433
- val_loss: 133.7968
Epoch 12/20
101/101 [==============================] - 201s 2s/step - loss: 111.4677
- val_loss: 131.8538
Epoch 13/20
101/101 [==============================] - 203s 2s/step - loss: 108.6516
- val_loss: 136.9488
Epoch 14/20
101/101 [==============================] - 201s 2s/step - loss: 105.6376
- val_loss: 131.5040
Epoch 15/20
101/101 [==============================] - 203s 2s/step - loss: 103.2039
- val_loss: 136.2721
Epoch 16/20
101/101 [==============================] - 203s 2s/step - loss: 101.5355
- val_loss: 128.7077
Epoch 17/20
101/101 [==============================] - 202s 2s/step - loss: 99.1531
- val_loss: 131.0174
Epoch 18/20
101/101 [==============================] - 202s 2s/step - loss: 97.0228
- val_loss: 132.4113
Epoch 19/20
101/101 [==============================] - 201s 2s/step - loss: 95.4892
- val_loss: 130.8649
Epoch 20/20
101/101 [==============================] - 202s 2s/step - loss: 94.9645
- val_loss: 131.1669
```

(IMPLEMENTATION) Model 4: Bidirectional RNN + TimeDistributed Dense

Read about the Bidirectional wrapper in the Keras documentation. For your next architecture, you will specify an architecture that uses a single bidirectional RNN layer, before a (`TimeDistributed`) dense layer. The added value of a bidirectional RNN is described well in this paper.

> One shortcoming of conventional RNNs is that they are only able to make use of previous context. In speech recognition, where whole utterances are transcribed at once, there is no reason not to exploit future context as well. Bidirectional RNNs (BRNNs) do this by processing the data in both directions with two separate hidden layers which are then fed forwards to the same output layer.

Before running the code cell below, you must complete the `bidirectional_rnn_model` function in `sample_models.py` . Feel free to use

`SimpleRNN`, `LSTM`, or `GRU` units. When specifying the `Bidirectional` wrapper, use `merge_mode='concat'`.

```
In [2]: model_4 = bidirectional_rnn_model(input_dim=161, # change to 13 if you wo
                                          units=200)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:488: The name tf.placeholder is deprecated. P
lease use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:63: The name tf.get_default_graph is deprecat
ed. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3626: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.


_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
bidirectional_1 (Bidirection (None, None, 400)         434400    
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 29)          11629     
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 446,029
Trainable params: 446,029
Non-trainable params: 0
_________________________________________________________________
None
```

Please execute the code cell below to train the neural network you specified in `input_to_softmax`. After the model has finished training, the model is saved in the HDF5 file `model_4.h5`. The loss history is saved in `model_4.pickle`. You are welcome to tweak any of the optional parameters while calling the `train_model` function, but this is not required.

```
In [3]: train_model(input_to_softmax=model_4,
                    pickle_path='model_4.pickle',
                    save_model_path='model_4.h5',
                    spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3741: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:711: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:949: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:936: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:158: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:172: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:180: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:187: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 196s 2s/step - loss: 267.0976
- val_loss: 231.5425
Epoch 2/20
101/101 [==============================] - 200s 2s/step - loss: 213.8051
- val_loss: 200.4790
Epoch 3/20
101/101 [==============================] - 199s 2s/step - loss: 201.1249
- val_loss: 195.0213
Epoch 4/20
101/101 [==============================] - 199s 2s/step - loss: 190.4837
- val_loss: 185.3153
Epoch 5/20
101/101 [==============================] - 199s 2s/step - loss: 182.2111
- val_loss: 178.3045
Epoch 6/20
101/101 [==============================] - 198s 2s/step - loss: 175.2863
- val_loss: 175.4351
Epoch 7/20
101/101 [==============================] - 199s 2s/step - loss: 168.5336
- val_loss: 164.5784
Epoch 8/20
101/101 [==============================] - 199s 2s/step - loss: 162.1646
- val_loss: 166.1030
Epoch 9/20
```

```
101/101 [==============================] - 200s 2s/step - loss: 156.4582
- val_loss: 159.0771
Epoch 10/20
101/101 [==============================] - 200s 2s/step - loss: 151.7594
- val_loss: 159.2844
Epoch 11/20
101/101 [==============================] - 198s 2s/step - loss: 146.8485
- val_loss: 154.6488
Epoch 12/20
101/101 [==============================] - 200s 2s/step - loss: 142.6537
- val_loss: 154.7036
Epoch 13/20
101/101 [==============================] - 199s 2s/step - loss: 139.0003
- val_loss: 150.8596
Epoch 14/20
101/101 [==============================] - 200s 2s/step - loss: 135.2226
- val_loss: 148.5861
Epoch 15/20
101/101 [==============================] - 200s 2s/step - loss: 131.5262
- val_loss: 148.4838
Epoch 16/20
101/101 [==============================] - 201s 2s/step - loss: 128.2652
- val_loss: 143.8347
Epoch 17/20
101/101 [==============================] - 199s 2s/step - loss: 125.4261
- val_loss: 148.9774
Epoch 18/20
101/101 [==============================] - 199s 2s/step - loss: 122.1960
- val_loss: 144.9319
Epoch 19/20
101/101 [==============================] - 200s 2s/step - loss: 119.3258
- val_loss: 144.7219
Epoch 20/20
101/101 [==============================] - 200s 2s/step - loss: 116.6334
- val_loss: 144.6623
```

(OPTIONAL IMPLEMENTATION) Models 5+

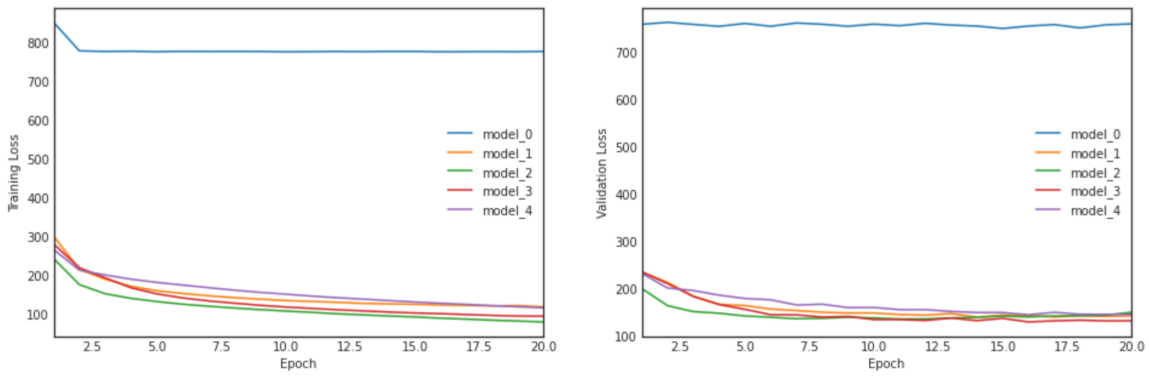
If you would like to try out more architectures than the ones above, please use the code cell below. Please continue to follow the same convention for saving the models; for the i-th sample model, please save the loss at `model_i.pickle` and saving the trained model at `model_i.h5`.

In [ ]:
```
## (Optional) TODO: Try out some more models!
### Feel free to use as many code cells as needed.
```

Compare the Models

Execute the code cell below to evaluate the performance of the drafted deep learning models. The training and validation loss are plotted for each model.

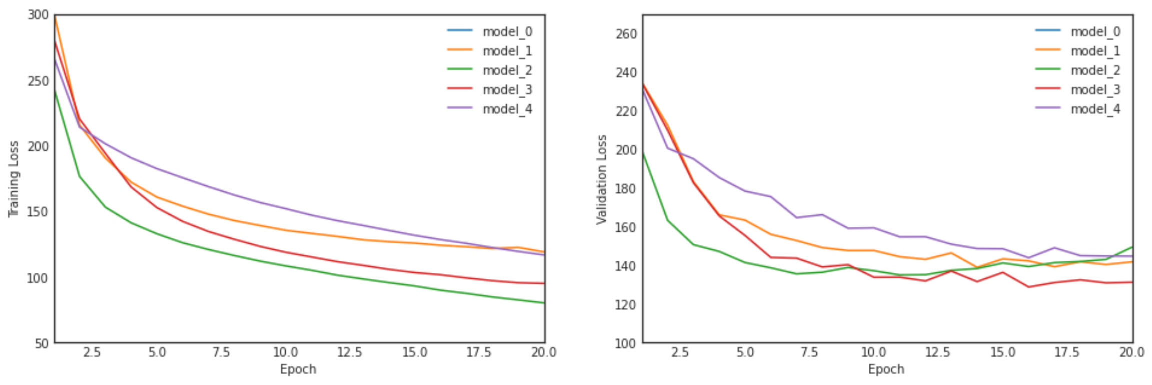
In [8]:
```
from glob import glob
import numpy as np
import _pickle as pickle
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set_style(style='white')

# obtain the paths for the saved model history
all_pickles = sorted(glob("results/*.pickle"))
# extract the name of each model
model_names = [item[8:-7] for item in all_pickles]
# extract the loss history for each model
valid_loss = [pickle.load( open( i, "rb" ) )['val_loss'] for i in all_pic
train_loss = [pickle.load( open( i, "rb" ) )['loss'] for i in all_pickles
# save the number of epochs used to train each model
num_epochs = [len(valid_loss[i]) for i in range(len(valid_loss))]

fig = plt.figure(figsize=(16,5))

# plot the training loss vs. epoch for each model
ax1 = fig.add_subplot(121)
for i in range(len(all_pickles)):
    ax1.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            train_loss[i], label=model_names[i])
# clean up the plot
ax1.legend()
ax1.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Training Loss')

# plot the validation loss vs. epoch for each model
ax2 = fig.add_subplot(122)
for i in range(len(all_pickles)):
    ax2.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            valid_loss[i], label=model_names[i])
# clean up the plot
ax2.legend()
ax2.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.show()
```



In [11]:

```
from glob import glob
import numpy as np
import _pickle as pickle
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set_style(style='white')
```

```
# obtain the paths for the saved model history
all_pickles = sorted(glob("results/*.pickle"))
# extract the name of each model
model_names = [item[8:-7] for item in all_pickles]
# extract the loss history for each model
valid_loss = [pickle.load( open( i, "rb" ) )['val_loss'] for i in all_pic
train_loss = [pickle.load( open( i, "rb" ) )['loss'] for i in all_pickles
# save the number of epochs used to train each model
num_epochs = [len(valid_loss[i]) for i in range(len(valid_loss))]

fig = plt.figure(figsize=(16,5))

# plot the training loss vs. epoch for each model
ax1 = fig.add_subplot(121)
for i in range(len(all_pickles)):
    ax1.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            train_loss[i], label=model_names[i])
# clean up the plot
ax1.legend()
ax1.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Training Loss')
plt.ylim(50, 300)

# plot the validation loss vs. epoch for each model
ax2 = fig.add_subplot(122)
for i in range(len(all_pickles)):
    ax2.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            valid_loss[i], label=model_names[i])
# clean up the plot
ax2.legend()
ax2.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.ylim(100, 270)
plt.show()
```



Question 1: Use the plot above to analyze the performance of each of the attempted architectures. Which performs best? Provide an explanation regarding why you think some models perform better than others.

Answer: Since Model 0 (RNN) tends to underfit, it can be seen that it is not a sufficient model to learn the features of the data. On the other hand, all other models show an overfit tendency because the valid loss starts to increase for training data up to 20 epochs. In particular, Model 2 (CNN + RNN + TimeDistributed Dense) shows a clear overfit tendency and records the minimum loss at the 7th epoch. All models except model 0 are likely to record less loss with appropriate regularization.

(IMPLEMENTATION) Final Model

Now that you've tried out many sample models, use what you've learned to draft your own architecture! While your final acoustic model should not be identical to any of the architectures explored above, you are welcome to merely combine the explored layers above into a deeper architecture. It is **NOT** necessary to include new layer types that were not explored in the notebook.

However, if you would like some ideas for even more layer types, check out these ideas for some additional, optional extensions to your model:

- If you notice your model is overfitting to the training dataset, consider adding **dropout**! To add dropout to recurrent layers, pay special attention to the `dropout_W` and `dropout_U` arguments. This paper may also provide some interesting theoretical background.
- If you choose to include a convolutional layer in your model, you may get better results by working with **dilated convolutions**. If you choose to use dilated convolutions, make sure that you are able to accurately calculate the length of the acoustic model's output in the `model.output_length` lambda function. You can read more about dilated convolutions in Google's WaveNet paper. For an example of a speech-to-text system that makes use of dilated convolutions, check out this GitHub repository. You can work with dilated convolutions in Keras by paying special attention to the `padding` argument when you specify a convolutional layer.
- If your model makes use of convolutional layers, why not also experiment with adding **max pooling**? Check out this paper for example architecture that makes use of max pooling in an acoustic model.
- So far, you have experimented with a single bidirectional RNN layer. Consider stacking the bidirectional layers, to produce a deep bidirectional RNN!

All models that you specify in this repository should have `output_length` defined as an attribute. This attribute is a lambda function that maps the (temporal) length of the input acoustic features to the (temporal) length of the output softmax layer. This function is used in the computation of CTC loss; to see this, look at the `add_ctc_loss` function in `train_utils.py`. To see where the `output_length` attribute is defined for the models in the code, take a look at the `sample_models.py` file. You will notice this line of code within most models:

```
model.output_length = lambda x: x
```

The acoustic model that incorporates a convolutional layer (`cnn_rnn_model`) has a line that is a bit different:

```
    model.output_length = lambda x: cnn_output_length(
            x, kernel_size, conv_border_mode, conv_stride)
```

In the case of models that use purely recurrent layers, the lambda function is the identity function, as the recurrent layers do not modify the (temporal) length of their input tensors. However, convolutional layers are more complicated and require a specialized function (`cnn_output_length` in `sample_models.py`) to determine the temporal length of their output.

You will have to add the `output_length` attribute to your final model before running the code cell below. Feel free to use the `cnn_output_length` function, if it suits your model.

In [1]:
```
#####################################################################
# RUN THIS CODE CELL IF YOU ARE RESUMING THE NOTEBOOK AFTER A BREAK #
#####################################################################

# allocate 50% of GPU memory (if you like, feel free to change this)
from keras.backend.tensorflow_backend import set_session
import tensorflow as tf
config = tf.ConfigProto()
config.gpu_options.per_process_gpu_memory_fraction = 0.5
set_session(tf.Session(config=config))

# watch for any changes in the sample_models module, and reload it automa
%load_ext autoreload
%autoreload 2
# import NN architectures for speech recognition
from sample_models import *
# import function for training acoustic model
from train_utils import train_model
```

```
WARNING:tensorflow:Deprecation warnings have been disabled. Set TF_ENABL
E_DEPRECATION_WARNINGS=1 to re-enable them.
Using TensorFlow backend.
```

In [2]:
```
# specify the model
model_end = final_model(input_dim=161, # change to 13 if you would like t
                        filters=200,
                        kernel_size=11,
                        conv_stride=2,
                        conv_border_mode='valid',
                        units=200,
                        recur_layers=2)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:488: The name tf.placeholder is deprecated. P
lease use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3626: The name tf.random_uniform is deprecate
d. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:117: The name tf.get_default_graph is depreca
ted. Please use tf.compat.v1.get_default_graph instead.
```

```
/home/sample_models.py:154: UserWarning: Update your `GRU` call to the K
eras 2 API: `GRU(200, activation="relu", return_sequences=True, name="rn
n_0", dropout=0.5, recurrent_dropout=0.5)`
  GRU(units, activation='relu', return_sequences=True, name='rnn_' + str
(ith),
/home/sample_models.py:154: UserWarning: Update your `GRU` call to the K
eras 2 API: `GRU(200, activation="relu", return_sequences=True, name="rn
n_1", dropout=0.5, recurrent_dropout=0.5)`
  GRU(units, activation='relu', return_sequences=True, name='rnn_' + str
(ith),
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
the_input (InputLayer)       (None, None, 161)         0
_________________________________________________________________
conv1d (Conv1D)              (None, None, 200)         354400
_________________________________________________________________
bn_conv_1d (BatchNormalizati (None, None, 200)         800
_________________________________________________________________
bidirectional_1 (Bidirection (None, None, 400)         481200
_________________________________________________________________
bn_rnn_1d_0 (BatchNormalizat (None, None, 400)         1600
_________________________________________________________________
bidirectional_2 (Bidirection (None, None, 400)         721200
_________________________________________________________________
bn_rnn_1d_1 (BatchNormalizat (None, None, 400)         1600
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 29)          11629
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0
=================================================================
Total params: 1,572,429
Trainable params: 1,570,429
Non-trainable params: 2,000
_________________________________________________________________
None
```

Please execute the code cell below to train the neural network you specified in `input_to_softmax`. After the model has finished training, the model is saved in the HDF5 file `model_end.h5`. The loss history is saved in `model_end.pickle`. You are welcome to tweak any of the optional parameters while calling the `train_model` function, but this is not required.

In [3]:
```
train_model(input_to_softmax=model_end,
            pickle_path='model_end.pickle',
            save_model_path='model_end.h5',
            spectrogram=True) # change to False if you would like to use
```

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:3741: The name tf.log is deprecated. Please u
se tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/opt
imizers.py:711: The name tf.train.Optimizer is deprecated. Please use t
f.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:949: The name tf.assign_add is deprecated. Pl
ease use tf.compat.v1.assign_add instead.

WARNING:tensorflow:Variable *= will be deprecated. Use `var.assign(var *
other)` if you want assignment to the variable value or `x = x * y` if y
ou want a new python Tensor object.
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:936: The name tf.assign is deprecated. Please
use tf.compat.v1.assign instead.

Epoch 1/20
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:158: The name tf.get_default_session is depre
cated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:172: The name tf.global_variables is deprecat
ed. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:180: The name tf.is_variable_initialized is d
eprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/keras/bac
kend/tensorflow_backend.py:187: The name tf.variables_initializer is dep
recated. Please use tf.compat.v1.variables_initializer instead.

101/101 [==============================] - 244s 2s/step - loss: 266.3081
- val_loss: 247.6694
Epoch 2/20
101/101 [==============================] - 235s 2s/step - loss: 232.3710
- val_loss: 223.8520
Epoch 3/20
101/101 [==============================] - 234s 2s/step - loss: 223.2239
- val_loss: 208.5439
Epoch 4/20
101/101 [==============================] - 232s 2s/step - loss: 204.7624
- val_loss: 187.1865
Epoch 5/20
101/101 [==============================] - 232s 2s/step - loss: 188.2542
- val_loss: 179.9056
Epoch 6/20
101/101 [==============================] - 234s 2s/step - loss: 177.0071
- val_loss: 166.6414
Epoch 7/20
101/101 [==============================] - 231s 2s/step - loss: 168.5004
- val_loss: 152.8091
Epoch 8/20
101/101 [==============================] - 233s 2s/step - loss: 162.5414
- val_loss: 145.5870
Epoch 9/20
```

```
101/101 [==============================] - 233s 2s/step - loss: 157.1442
- val_loss: 142.2745
Epoch 10/20
101/101 [==============================] - 232s 2s/step - loss: 152.8202
- val_loss: 139.2816
Epoch 11/20
101/101 [==============================] - 233s 2s/step - loss: 149.7545
- val_loss: 135.7911
Epoch 12/20
101/101 [==============================] - 233s 2s/step - loss: 145.9477
- val_loss: 134.8015
Epoch 13/20
101/101 [==============================] - 232s 2s/step - loss: 142.9725
- val_loss: 130.6167
Epoch 14/20
101/101 [==============================] - 233s 2s/step - loss: 140.2559
- val_loss: 130.0604
Epoch 15/20
101/101 [==============================] - 232s 2s/step - loss: 137.8361
- val_loss: 126.6415
Epoch 16/20
101/101 [==============================] - 233s 2s/step - loss: 135.7143
- val_loss: 124.7123
Epoch 17/20
101/101 [==============================] - 232s 2s/step - loss: 133.4858
- val_loss: 124.3876
Epoch 18/20
101/101 [==============================] - 232s 2s/step - loss: 131.8432
- val_loss: 121.8541
Epoch 19/20
101/101 [==============================] - 233s 2s/step - loss: 129.8456
- val_loss: 120.8134
Epoch 20/20
101/101 [==============================] - 233s 2s/step - loss: 128.0450
- val_loss: 120.9789
```

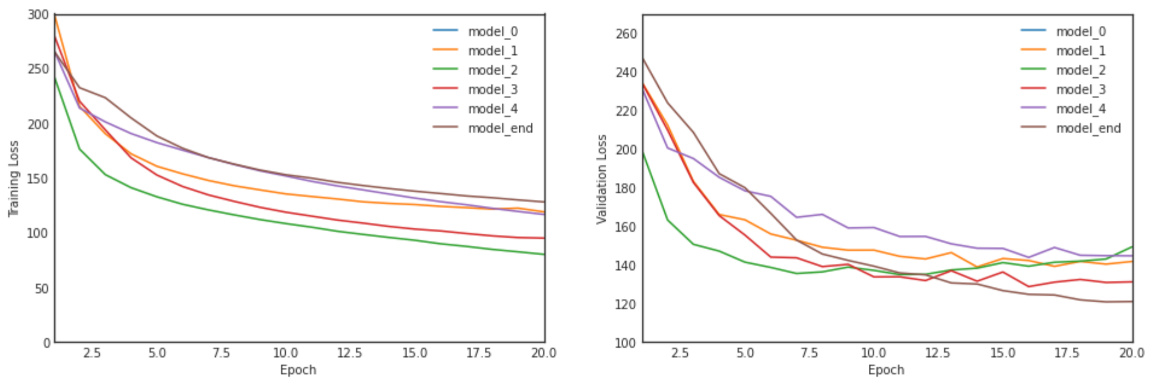
Question 2: Describe your final model architecture and your reasoning at each step.

Answer: My final model consists of a multi-layer CNN, a bidirectional RNN, and a `TimeDistributedDNN`. As can be easily predicted in the first training, at the 4th epoch, the valid loss stopped monotonically decreasing and gradually increased overfit. The minimum valid loss was 127.0196 in the 7th epoch.

It effectively alleviated the overfit by adding dropout using the dropout of the recurrent layer. If 0.5 is given for both the `dropout_U` and `dropout_W` parameters, the minimum value of the valid loss is 121.3858, and it is recorded at the 20th epoch.

In [4]:
```
from glob import glob
import numpy as np
import _pickle as pickle
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set_style(style='white')

# obtain the paths for the saved model history
```

```
all_pickles = sorted(glob("results/*.pickle"))
# extract the name of each model
model_names = [item[8:-7] for item in all_pickles]
# extract the loss history for each model
valid_loss = [pickle.load( open( i, "rb" ) )['val_loss'] for i in all_pic
train_loss = [pickle.load( open( i, "rb" ) )['loss'] for i in all_pickles
# save the number of epochs used to train each model
num_epochs = [len(valid_loss[i]) for i in range(len(valid_loss))]

fig = plt.figure(figsize=(16,5))

# plot the training loss vs. epoch for each model
ax1 = fig.add_subplot(121)
for i in range(len(all_pickles)):
    ax1.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            train_loss[i], label=model_names[i])
# clean up the plot
ax1.legend()
ax1.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Training Loss')
plt.ylim(0, 300)

# plot the validation loss vs. epoch for each model
ax2 = fig.add_subplot(122)
for i in range(len(all_pickles)):
    ax2.plot(np.linspace(1, num_epochs[i], num_epochs[i]),
            valid_loss[i], label=model_names[i])
# clean up the plot
ax2.legend()
ax2.set_xlim([1, max(num_epochs)])
plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.ylim(100, 270)
plt.show()
```



STEP 3: Obtain Predictions

We have written a function for you to decode the predictions of your acoustic model. To use the function, please execute the code cell below.

In [5]:
```
import numpy as np
from data_generator import AudioGenerator
from keras import backend as K
from utils import int_sequence_to_text
from IPython.display import Audio

def get_predictions(index, partition, input_to_softmax, model_path):
    """ Print a model's decoded predictions
    Params:
        index (int): The example you would like to visualize
        partition (str): One of 'train' or 'validation'
        input_to_softmax (Model): The acoustic model
        model_path (str): Path to saved acoustic model's weights
    """
    # load the train and test data
    data_gen = AudioGenerator()
    data_gen.load_train_data()
    data_gen.load_validation_data()

    # obtain the true transcription and the audio features
    if partition == 'validation':
        transcr = data_gen.valid_texts[index]
        audio_path = data_gen.valid_audio_paths[index]
        data_point = data_gen.normalize(data_gen.featurize(audio_path))
    elif partition == 'train':
        transcr = data_gen.train_texts[index]
        audio_path = data_gen.train_audio_paths[index]
        data_point = data_gen.normalize(data_gen.featurize(audio_path))
    else:
        raise Exception('Invalid partition!  Must be "train" or "validati

    # obtain and decode the acoustic model's predictions
    input_to_softmax.load_weights(os.path.join('results', model_path))
    prediction = input_to_softmax.predict(np.expand_dims(data_point, axis
    output_length = [input_to_softmax.output_length(data_point.shape[0])]
    pred_ints = (K.eval(K.ctc_decode(
                prediction, output_length)[0][0])+1).flatten().tolist()

    # play the audio file, and display the true and predicted transcripti
    print('-'*80)
    Audio(audio_path)
    print('True transcription:\n' + '\n' + transcr)
    print('-'*80)
    print('Predicted transcription:\n' + '\n' + ''.join(int_sequence_to_t
    print('-'*80)
```

Use the code cell below to obtain the transcription predicted by your final model for the first example in the training dataset.

```
In [6]: get_predictions(index=0,
                        partition='train',
                        input_to_softmax=final_model(input_dim=161, filters=200,
                                conv_border_mode='valid', units=200, recur_layers
                        model_path='model_end.h5')
```

```
/home/sample_models.py:154: UserWarning: Update your `GRU` call to the K
eras 2 API: `GRU(200, activation="relu", return_sequences=True, name="rn
n_0", dropout=0.5, recurrent_dropout=0.5)`
  GRU(units, activation='relu', return_sequences=True, name='rnn_' + str
(ith),
/home/sample_models.py:154: UserWarning: Update your `GRU` call to the K
eras 2 API: `GRU(200, activation="relu", return_sequences=True, name="rn
n_1", dropout=0.5, recurrent_dropout=0.5)`
  GRU(units, activation='relu', return_sequences=True, name='rnn_' + str
(ith),
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
conv1d (Conv1D)              (None, None, 200)         354400    
_________________________________________________________________
bn_conv_1d (BatchNormalizati (None, None, 200)         800       
_________________________________________________________________
bidirectional_3 (Bidirection (None, None, 400)         481200    
_________________________________________________________________
bn_rnn_1d_0 (BatchNormalizat (None, None, 400)         1600      
_________________________________________________________________
bidirectional_4 (Bidirection (None, None, 400)         721200    
_________________________________________________________________
bn_rnn_1d_1 (BatchNormalizat (None, None, 400)         1600      
_________________________________________________________________
time_distributed_2 (TimeDist (None, None, 29)          11629     
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 1,572,429
Trainable params: 1,570,429
Non-trainable params: 2,000
_________________________________________________________________
None
------------------------------------------------------------------------
--------
True transcription:

her father is a most remarkable person to say the least
------------------------------------------------------------------------
--------
Predicted transcription:

e fotthers am mos fr mor a bo porsin to sathe lest
------------------------------------------------------------------------
--------
```

Use the next code cell to visualize the model's prediction for the first example in the validation dataset.

In [7]:
```
get_predictions(index=0,
                partition='validation',
                input_to_softmax=final_model(input_dim=161, filters=200,
                        conv_border_mode='valid', units=200, recur_layers
                model_path='model_end.h5')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
the_input (InputLayer)       (None, None, 161)         0         
_________________________________________________________________
conv1d (Conv1D)              (None, None, 200)         354400    
_________________________________________________________________
bn_conv_1d (BatchNormalizati (None, None, 200)         800       
_________________________________________________________________
bidirectional_5 (Bidirection (None, None, 400)         481200    
_________________________________________________________________
bn_rnn_1d_0 (BatchNormalizat (None, None, 400)         1600      
_________________________________________________________________
bidirectional_6 (Bidirection (None, None, 400)         721200    
_________________________________________________________________
bn_rnn_1d_1 (BatchNormalizat (None, None, 400)         1600      
_________________________________________________________________
time_distributed_3 (TimeDist (None, None, 29)          11629     
_________________________________________________________________
softmax (Activation)         (None, None, 29)          0         
=================================================================
Total params: 1,572,429
Trainable params: 1,570,429
Non-trainable params: 2,000
_________________________________________________________________
None
------------------------------------------------------------------------
--------
True transcription:

the bogus legislature numbered thirty six members
------------------------------------------------------------------------
--------
Predicted transcription:

the bel lhis or dis latur nomver tery ses memers
------------------------------------------------------------------------
--------
```

One standard way to improve the results of the decoder is to incorporate a language model. We won't pursue this in the notebook, but you are welcome to do so as an *optional extension*.

If you are interested in creating models that provide improved transcriptions, you are encouraged to download more data and train bigger, deeper models. But beware - the model will likely take a long while to train. For instance, training this state-of-the-art model would take 3-6 weeks on a single GPU!