

# Trigger\_word\_detection\_v1a

April 22, 2021

## 0.1 Trigger Word Detection

Welcome to the final programming assignment of this specialization!

In this week's videos, you learned about applying deep learning to speech recognition. In this assignment, you will construct a speech dataset and implement an algorithm for trigger word detection (sometimes also called keyword detection, or wake word detection).

- Trigger word detection is the technology that allows devices like Amazon Alexa, Google Home, Apple Siri, and Baidu DuerOS to wake up upon hearing a certain word.
- For this exercise, our trigger word will be "Activate." Every time it hears you say "activate," it will make a "chiming" sound.
- By the end of this assignment, you will be able to record a clip of yourself talking, and have the algorithm trigger a chime when it detects you saying "activate."
- After completing this assignment, perhaps you can also extend it to run on your laptop so that every time you say "activate" it starts up your favorite app, or turns on a network connected lamp in your house, or triggers some other event?

In this assignment you will learn to: - Structure a speech recognition project - Synthesize and process audio recordings to create train/dev datasets - Train a trigger word detection model and make predictions

## 0.2 Updates

**If you were working on the notebook before this update...**

- The current notebook is version "1a".
- You can find your original work saved in the notebook with the previous version name ("v1")
- To view the file directory, go to the menu "File->Open", and this will open a new tab that shows the file directory.

### List of updates

- 2.1: build the model
  - Added sample code to show how to use the Keras layers.
  - Lets student to implement the TimeDistributed code.

- Spelling, grammar and wording corrections.

Let's get started! Run the following cell to load the package you are going to use.

```
In [1]: import numpy as np
        from pydub import AudioSegment
        import random
        import sys
        import io
        import os
        import glob
        import IPython
        from td_utils import *
        %matplotlib inline
```

## 1 1 - Data synthesis: Creating a speech dataset

Let's start by building a dataset for your trigger word detection algorithm. \* A speech dataset should ideally be as close as possible to the application you will want to run it on. \* In this case, you'd like to detect the word "activate" in working environments (library, home, offices, open-spaces ...). \* Therefore, you need to create recordings with a mix of positive words ("activate") and negative words (random words other than activate) on different background sounds. Let's see how you can create such a dataset.

### 1.1 1.1 - Listening to the data

- One of your friends is helping you out on this project, and they've gone to libraries, cafes, restaurants, homes and offices all around the region to record background noises, as well as snippets of audio of people saying positive/negative words. This dataset includes people speaking in a variety of accents.
- In the raw\_data directory, you can find a subset of the raw audio files of the positive words, negative words, and background noise. You will use these audio files to synthesize a dataset to train the model.
  - The "activate" directory contains positive examples of people saying the word "activate".
  - The "negatives" directory contains negative examples of people saying random words other than "activate".
  - There is one word per audio recording.
  - The "backgrounds" directory contains 10 second clips of background noise in different environments.

Run the cells below to listen to some examples.

```
In [2]: IPython.display.Audio("./raw_data/activates/1.wav")
```

```
Out[2]: <IPython.lib.display.Audio object>
```

```
In [3]: IPython.display.Audio("./raw_data/negatives/4.wav")
```

```
Out [3]: <IPython.lib.display.Audio object>
```

```
In [4]: IPython.display.Audio("./raw_data/backgrounds/1.wav")
```

```
Out [4]: <IPython.lib.display.Audio object>
```

You will use these three types of recordings (positives/negatives/backgrounds) to create a labeled dataset.

## 1.2 1.2 - From audio recordings to spectrograms

What really is an audio recording? \* A microphone records little variations in air pressure over time, and it is these little variations in air pressure that your ear also perceives as sound. \* You can think of an audio recording is a long list of numbers measuring the little air pressure changes detected by the microphone. \* We will use audio sampled at 44100 Hz (or 44100 Hertz). \* This means the microphone gives us 44,100 numbers per second. \* Thus, a 10 second audio clip is represented by 441,000 numbers ( $= 10 \times 44,100$ ).

### Spectrogram

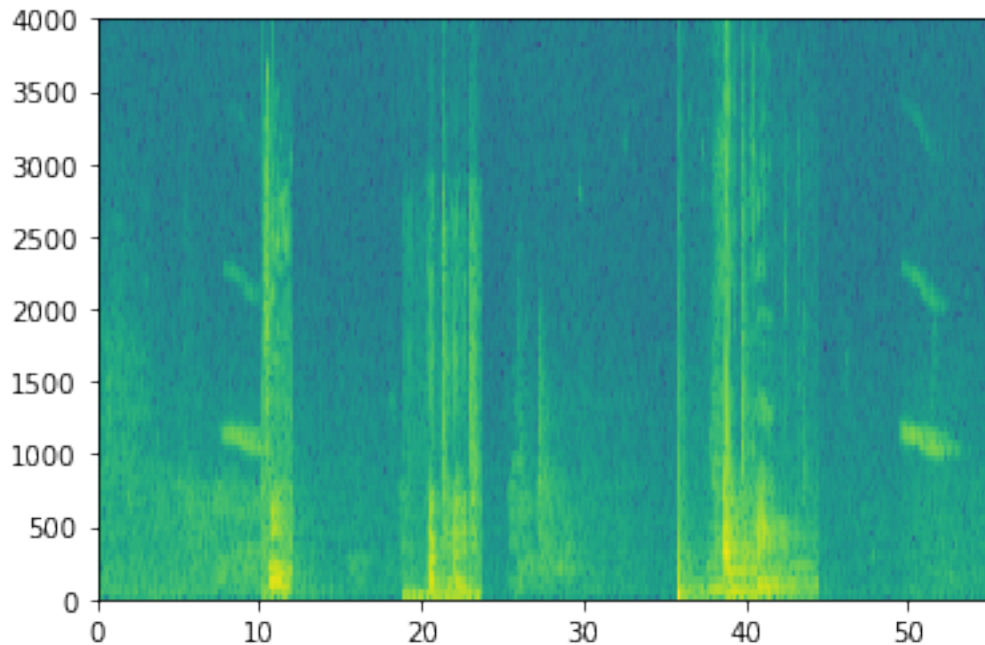
- It is quite difficult to figure out from this “raw” representation of audio whether the word “activate” was said.
- In order to help your sequence model more easily learn to detect trigger words, we will compute a *spectrogram* of the audio.
- The spectrogram tells us how much different frequencies are present in an audio clip at any moment in time.
- If you’ve ever taken an advanced class on signal processing or on Fourier transforms:
  - A spectrogram is computed by sliding a window over the raw audio signal, and calculating the most active frequencies in each window using a Fourier transform.
  - If you don’t understand the previous sentence, don’t worry about it.

Let’s look at an example.

```
In [5]: IPython.display.Audio("audio_examples/example_train.wav")
```

```
Out [5]: <IPython.lib.display.Audio object>
```

```
In [6]: x = graph_spectrogram("audio_examples/example_train.wav")
```



The graph above represents how active each frequency is (y axis) over a number of time-steps (x axis).

**Figure 1:** Spectrogram of an audio recording

- The color in the spectrogram shows the degree to which different frequencies are present (loud) in the audio at different points in time.
- Green means a certain frequency is more active or more present in the audio clip (louder).
- Blue squares denote less active frequencies.
- The dimension of the output spectrogram depends upon the hyperparameters of the spectrogram software and the length of the input.
- In this notebook, we will be working with 10 second audio clips as the “standard length” for our training examples.
  - The number of timesteps of the spectrogram will be 5511.
  - You’ll see later that the spectrogram will be the input  $x$  into the network, and so  $T_x = 5511$ .

```
In [7]: _, data = wavfile.read("audio_examples/example_train.wav")
        print("Time steps in audio recording before spectrogram", data[:,0].shape)
        print("Time steps in input after spectrogram", x.shape)
```

```
Time steps in audio recording before spectrogram (441000,)
Time steps in input after spectrogram (101, 5511)
```

Now, you can define:

```
In [8]: Tx = 5511 # The number of time steps input to the model from the spectrogram
        n_freq = 101 # Number of frequencies input to the model at each time step
```

**Dividing into time-intervals** Note that we may divide a 10 second interval of time with different units (steps). \* Raw audio divides 10 seconds into 441,000 units. \* A spectrogram divides 10 seconds into 5,511 units. \*  $T_x = 5511$  \* You will use a Python module `pydub` to synthesize audio, and it divides 10 seconds into 10,000 units. \* The output of our model will divide 10 seconds into 1,375 units. \*  $T_y = 1375$  \* For each of the 1375 time steps, the model predicts whether someone recently finished saying the trigger word “activate.” \* All of these are hyperparameters and can be changed (except the 441000, which is a function of the microphone). \* We have chosen values that are within the standard range used for speech systems.

```
In [9]: Ty = 1375 # The number of time steps in the output of our model
```

### 1.3 - Generating a single training example

**Benefits of synthesizing data** Because speech data is hard to acquire and label, you will synthesize your training data using the audio clips of activates, negatives, and backgrounds. \* It is quite slow to record lots of 10 second audio clips with random “activates” in it. \* Instead, it is easier to record lots of positives and negative words, and record background noise separately (or download background noise from free online sources).

#### Process for Synthesizing an audio clip

- To synthesize a single training example, you will:
  - Pick a random 10 second background audio clip
  - Randomly insert 0-4 audio clips of “activate” into this 10sec clip
  - Randomly insert 0-2 audio clips of negative words into this 10sec clip
- Because you had synthesized the word “activate” into the background clip, you know exactly when in the 10 second clip the “activate” makes its appearance.
  - You’ll see later that this makes it easier to generate the labels  $y^{(t)}$  as well.

#### Pydub

- You will use the `pydub` package to manipulate audio.
- `Pydub` converts raw audio files into lists of `Pydub` data structures.
  - Don’t worry about the details of the data structures.
- `Pydub` uses 1ms as the discretization interval (1ms is 1 millisecond = 1/1000 seconds).
  - This is why a 10 second clip is always represented using 10,000 steps.

```
In [10]: # Load audio segments using pydub
         activates, negatives, backgrounds = load_raw_audio()

         print("background len should be 10,000, since it is a 10 sec clip\n" + str(len(backgrounds)))
         print("activate[0] len may be around 1000, since an `activate` audio clip has len around 1000")
         print("activate[1] len: different `activate` clips can have different lengths")
```

background len should be 10,000, since it is a 10 sec clip  
10000

activate[0] len may be around 1000, since an `activate` audio clip is usually around  
916

activate[1] len: different `activate` clips can have different lengths  
1579

### 1.3.1 Overlaying positive/negative 'word' audio clips on top of the background audio

- Given a 10 second background clip and a short audio clip containing a positive or negative word, you need to be able to "add" the word audio clip on top of the background audio.
- You will be inserting multiple clips of positive/negative words into the background, and you don't want to insert an "activate" or a random word somewhere that overlaps with another clip you had previously added.
  - To ensure that the 'word' audio segments do not overlap when inserted, you will keep track of the times of previously inserted audio clips.
- To be clear, when you insert a 1 second "activate" onto a 10 second clip of cafe noise, **you do not end up with an 11 sec clip.**
  - The resulting audio clip is still 10 seconds long.
  - You'll see later how pydub allows you to do this.

#### Label the positive/negative words

- Recall that the labels  $y^{(t)}$  represent whether or not someone has just finished saying "activate."
  - $y^{(t)} = 1$  when that clip has finished saying "activate".
  - Given a background clip, we can initialize  $y^{(t)} = 0$  for all  $t$ , since the clip doesn't contain any "activates."
- When you insert or overlay an "activate" clip, you will also update labels for  $y^{(t)}$ .
  - Rather than updating the label of a single time step, we will update 50 steps of the output to have target label 1.
  - Recall from the lecture on trigger word detection that updating several consecutive time steps can make the training data more balanced.
- You will train a GRU (Gated Recurrent Unit) to detect when someone has **finished** saying "activate".

#### Example

- Suppose the synthesized "activate" clip ends at the 5 second mark in the 10 second audio - exactly halfway into the clip.

- Recall that  $T_y = 1375$ , so timestep  $687 = \text{int}(1375 * 0.5)$  corresponds to the moment 5 seconds into the audio clip.
- Set  $y^{(688)} = 1$ .
- We will allow the GRU to detect “activate” anywhere within a short time-interval **after** this moment, so we actually **set 50 consecutive values** of the label  $y^{(t)}$  to 1.
  - Specifically, we have  $y^{(688)} = y^{(689)} = \dots = y^{(737)} = 1$ .

### Synthesized data is easier to label

- This is another reason for synthesizing the training data: It’s relatively straightforward to generate these labels  $y^{(t)}$  as described above.
- In contrast, if you have 10sec of audio recorded on a microphone, it’s quite time consuming for a person to listen to it and mark manually exactly when “activate” finished.

### Visualizing the labels

- Here’s a figure illustrating the labels  $y^{(t)}$  in a clip.
  - We have inserted “activate”, “innocent”, activate”, “baby.”
  - Note that the positive labels “1” are associated only with the positive words.

Figure 2

**Helper functions** To implement the training set synthesis process, you will use the following helper functions. \* All of these functions will use a 1ms discretization interval \* The 10 seconds of audio is always discretized into 10,000 steps.

1. `get_random_time_segment(segment_ms)`
  - Retrieves a random time segment from the background audio.
2. `is_overlapping(segment_time, existing_segments)`
  - Checks if a time segment overlaps with existing segments
3. `insert_audio_clip(background, audio_clip, existing_times)`
  - Inserts an audio segment at a random time in the background audio
  - Uses the functions `get_random_time_segment` and `is_overlapping`
4. `insert_ones(y, segment_end_ms)`
  - Inserts additional 1’s into the label vector `y` after the word “activate”

### Get a random time segment

- The function `get_random_time_segment(segment_ms)` returns a random time segment onto which we can insert an audio clip of duration `segment_ms`.
- Please read through the code to make sure you understand what it is doing.

```
In [11]: def get_random_time_segment(segment_ms):
        """
        Gets a random time segment of duration segment_ms in a 10,000 ms audio clip.

        Arguments:
        segment_ms -- the duration of the audio clip in ms ("ms" stands for "milliseconds")

        Returns:
        segment_time -- a tuple of (segment_start, segment_end) in ms
        """

        segment_start = np.random.randint(low=0, high=10000-segment_ms) # Make sure the segment_end is not out of bounds
        segment_end = segment_start + segment_ms - 1

        return (segment_start, segment_end)
```

### Check if audio clips are overlapping

- Suppose you have inserted audio clips at segments (1000,1800) and (3400,4500).
  - The first segment starts at step 1000 and ends at step 1800.
  - The second segment starts at 3400 and ends at 4500.
- If we are considering whether to insert a new audio clip at (3000,3600) does this overlap with one of the previously inserted segments?
  - In this case, (3000,3600) and (3400,4500) overlap, so we should decide against inserting a clip here.
- For the purpose of this function, define (100,200) and (200,250) to be overlapping, since they overlap at timestep 200.
- (100,199) and (200,250) are non-overlapping.

**Exercise:** \* Implement `is_overlapping(segment_time, existing_segments)` to check if a new time segment overlaps with any of the previous segments. \* You will need to carry out 2 steps:

1. Create a “False” flag, that you will later set to “True” if you find that there is an overlap.
2. Loop over the previous\_segments’ start and end times. Compare these times to the segment’s start and end times. If there is an overlap, set the flag defined in (1) as True.

You can use:

```
for ...:
    if ... <= ... and ... >= ...:
        ...
```

Hint: There is overlap if: \* The new segment starts before the previous segment ends **and** \* The new segment ends after the previous segment starts.



```
In [12]: # GRADED FUNCTION: is_overlapping
```

```
def is_overlapping(segment_time, previous_segments):
    """
    Checks if the time of a segment overlaps with the times of existing segments.

    Arguments:
    segment_time -- a tuple of (segment_start, segment_end) for the new segment
    previous_segments -- a list of tuples of (segment_start, segment_end) for the previous segments

    Returns:
    True if the time segment overlaps with any of the existing segments, False otherwise.
    """

    segment_start, segment_end = segment_time

    ### START CODE HERE ### (≈ 4 lines)
    # Step 1: Initialize overlap as a "False" flag. (≈ 1 line)
    overlap = False

    # Step 2: loop over the previous_segments start and end times.
    # Compare start/end times and set the flag to True if there is an overlap
    for previous_start, previous_end in previous_segments:
        if segment_start <= previous_end and segment_end >= previous_start:
            overlap = True
    ### END CODE HERE ###

    return overlap
```

```
In [13]: overlap1 = is_overlapping((950, 1430), [(2000, 2550), (260, 949)])
         overlap2 = is_overlapping((2305, 2950), [(824, 1532), (1900, 2305), (3424, 4131)])
         print("Overlap 1 = ", overlap1)
         print("Overlap 2 = ", overlap2)
```

```
Overlap 1 = False
```

```
Overlap 2 = True
```

### Expected Output:

**Overlap 1**

False

**Overlap 2**

True

### Insert audio clip

- Let's use the previous helper functions to insert a new audio clip onto the 10 second background at a random time.

- We will ensure that any newly inserted segment doesn't overlap with previously inserted segments.

**Exercise:** \* Implement `insert_audio_clip()` to overlay an audio clip onto the background 10sec clip. \* You implement 4 steps:

1. Get the length of the audio clip that is to be inserted.
  - Get a random time segment whose duration equals the duration of the audio clip that is to be inserted.
2. Make sure that the time segment does not overlap with any of the previous time segments.
  - If it is overlapping, then go back to step 1 and pick a new time segment.
3. Append the new time segment to the list of existing time segments
  - This keeps track of all the segments you've inserted.
4. Overlay the audio clip over the background using `pydub`. We have implemented this for you.

In [14]: # GRADED FUNCTION: `insert_audio_clip`

```
def insert_audio_clip(background, audio_clip, previous_segments):
    """
    Insert a new audio segment over the background noise at a random time
    audio segment does not overlap with existing segments.

    Arguments:
    background -- a 10 second background audio recording.
    audio_clip -- the audio clip to be inserted/overlaid.
    previous_segments -- times where audio segments have already been placed

    Returns:
    new_background -- the updated background audio
    """

    # Get the duration of the audio clip in ms
    segment_ms = len(audio_clip)

    ### START CODE HERE ###
    # Step 1: Use one of the helper functions to pick a random time segment
    # the new audio clip. (≈ 1 line)
    segment_time = get_random_time_segment(segment_ms)

    # Step 2: Check if the new segment_time overlaps with one of the previous
    # picking new segment_time at random until it doesn't overlap. (≈ 2 lines)
    while is_overlapping(segment_time, previous_segments):
        segment_time = get_random_time_segment(segment_ms)
```

```

# Step 3: Append the new segment_time to the list of previous_segments
previous_segments.append(segment_time)
### END CODE HERE ###

# Step 4: Superpose audio segment and background
new_background = background.overlay(audio_clip, position = segment_time)

return new_background, segment_time

```

```

In [15]: np.random.seed(5)
         audio_clip, segment_time = insert_audio_clip(backgrounds[0], activates[0],
         audio_clip.export("insert_test.wav", format="wav")
         print("Segment Time: ", segment_time)
         IPython.display.Audio("insert_test.wav")

```

Segment Time: (2254, 3169)

Out[15]: <IPython.lib.display.Audio object>

**Expected Output**  
**Segment Time**  
(2254, 3169)

```

In [16]: # Expected audio
         IPython.display.Audio("audio_examples/insert_reference.wav")

```

Out[16]: <IPython.lib.display.Audio object>

### Insert ones for the labels of the positive target

- Implement code to update the labels  $y^{(t)}$ , assuming you just inserted an “activate” audio clip.
- In the code below,  $y$  is a  $(1, 1375)$  dimensional vector, since  $T_y = 1375$ .
- If the “activate” audio clip ends at time step  $t$ , then set  $y^{(t+1)} = 1$  and also set the next 49 additional consecutive values to 1.
  - Notice that if the target word appears near the end of the entire audio clip, there may not be 50 additional time steps to set to 1.
  - Make sure you don’t run off the end of the array and try to update  $y[0][1375]$ , since the valid indices are  $y[0][0]$  through  $y[0][1374]$  because  $T_y = 1375$ .
  - So if “activate” ends at step 1370, you would get only set  $y[0][1371] = y[0][1372] = y[0][1373] = y[0][1374] = 1$

**Exercise:** Implement `insert_ones()`. \* You can use a for loop. \* If you want to use Python’s array slicing operations, you can do so as well. \* If a segment ends at `segment_end_ms` (using a 10000 step discretization), \* To convert it to the indexing for the outputs  $y$  (using a 1375 step discretization), we will use this formula:

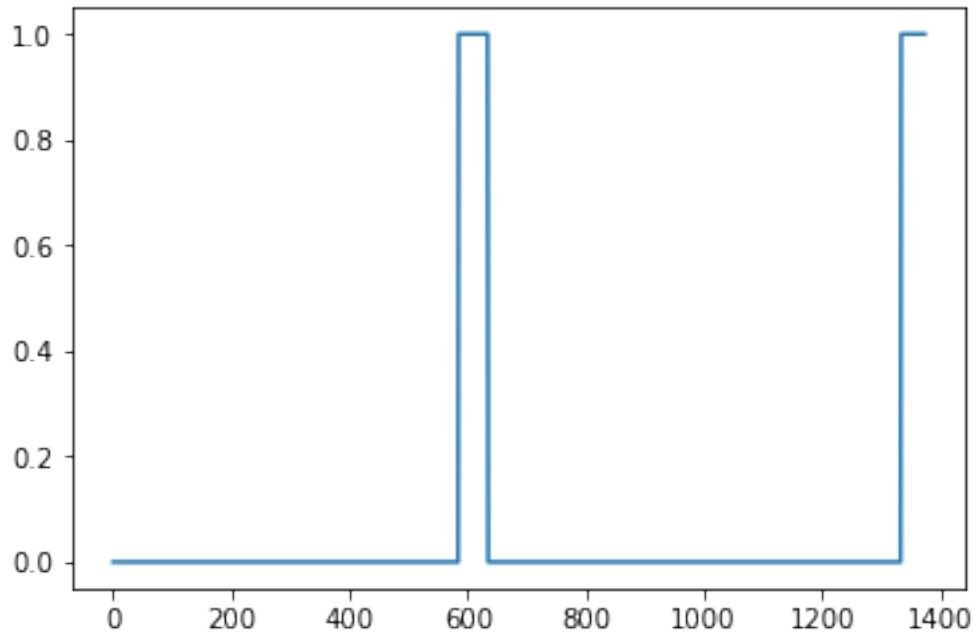
```
segment_end_y = int(segment_end_ms * Ty / 10000.0)
```

```
In [17]: # GRADED FUNCTION: insert_ones
```

```
def insert_ones(y, segment_end_ms):  
    """  
    Update the label vector y. The labels of the 50 output steps strictly  
    should be set to 1. By strictly we mean that the label of segment_end  
    50 following labels should be ones.  
  
    Arguments:  
    y -- numpy array of shape (1, Ty), the labels of the training example  
    segment_end_ms -- the end time of the segment in ms  
  
    Returns:  
    y -- updated labels  
    """  
  
    # duration of the background (in terms of spectrogram time-steps)  
    segment_end_y = int(segment_end_ms * Ty / 10000.0)  
  
    # Add 1 to the correct index in the background label (y)  
    ### START CODE HERE ### (~ 3 lines)  
    for i in range(segment_end_y + 1, segment_end_y + 51):  
        if i < Ty:  
            y[0, i] = 1  
    ### END CODE HERE ###  
  
    return y
```

```
In [18]: arr1 = insert_ones(np.zeros((1, Ty)), 9700)  
         plt.plot(insert_ones(arr1, 4251)[0,:])  
         print("sanity checks:", arr1[0][1333], arr1[0][634], arr1[0][635])
```

```
sanity checks: 0.0 1.0 0.0
```



### Expected Output

sanity checks:

0.0 1.0 0.0

**Creating a training example** Finally, you can use `insert_audio_clip` and `insert_ones` to create a new training example.

**Exercise:** Implement `create_training_example()`. You will need to carry out the following steps:

1. Initialize the label vector  $y$  as a numpy array of zeros and shape  $(1, T_y)$ .
2. Initialize the set of existing segments to an empty list.
3. Randomly select 0 to 4 “activate” audio clips, and insert them onto the 10 second clip. Also insert labels at the correct position in the label vector  $y$ .
4. Randomly select 0 to 2 negative audio clips, and insert them into the 10 second clip.

In [19]: # GRADED FUNCTION: `create_training_example`

```
def create_training_example(background, activates, negatives):
    """
    Creates a training example with a given background, activates, and negatives.

    Arguments:
    background -- a 10 second background audio recording
    activates -- a list of audio segments of the word "activate"
    negatives -- a list of audio segments of random words that are not "activate"
```

*Returns:*

*x -- the spectrogram of the training example*  
*y -- the label at each time step of the spectrogram*  
"""

*# Set the random seed*

np.random.seed(18)

*# Make background quieter*

background = background - 20

### START CODE HERE ###

*# Step 1: Initialize y (label vector) of zeros ( $\approx 1$  line)*

y = np.zeros((1, Ty))

*# Step 2: Initialize segment times as an empty list ( $\approx 1$  line)*

previous\_segments = []

### END CODE HERE ###

*# Select 0-4 random "activate" audio clips from the entire list of "a*

number\_of\_activates = np.random.randint(0, 5)

random\_indices = np.random.randint(len(activates), size=number\_of\_acti

random\_activates = [activates[i] for i in random\_indices]

### START CODE HERE ### ( $\approx 3$  lines)

*# Step 3: Loop over randomly selected "activate" clips and insert in k*

for random\_activate in random\_activates:

*# Insert the audio clip on the background*

background, segment\_time = insert\_audio\_clip(background, random\_ac

*# Retrieve segment\_start and segment\_end from segment\_time*

segment\_start, segment\_end = segment\_time

*# Insert labels in "y"*

y = insert\_ones(y, segment\_end\_ms=segment\_end)

### END CODE HERE ###

*# Select 0-2 random negatives audio recordings from the entire list of*

number\_of\_negatives = np.random.randint(0, 3)

random\_indices = np.random.randint(len(negatives), size=number\_of\_neg

random\_negatives = [negatives[i] for i in random\_indices]

### START CODE HERE ### ( $\approx 2$  lines)

*# Step 4: Loop over randomly selected negative clips and insert in bac*

for random\_negative in random\_negatives:

*# Insert the audio clip on the background*

background, \_ = insert\_audio\_clip(background, random\_negative, pre

### END CODE HERE ###

*# Standardize the volume of the audio clip*

```

background = match_target_amplitude(background, -20.0)

# Export new training example
file_handle = background.export("train" + ".wav", format="wav")
print("File (train.wav) was saved in your directory.")

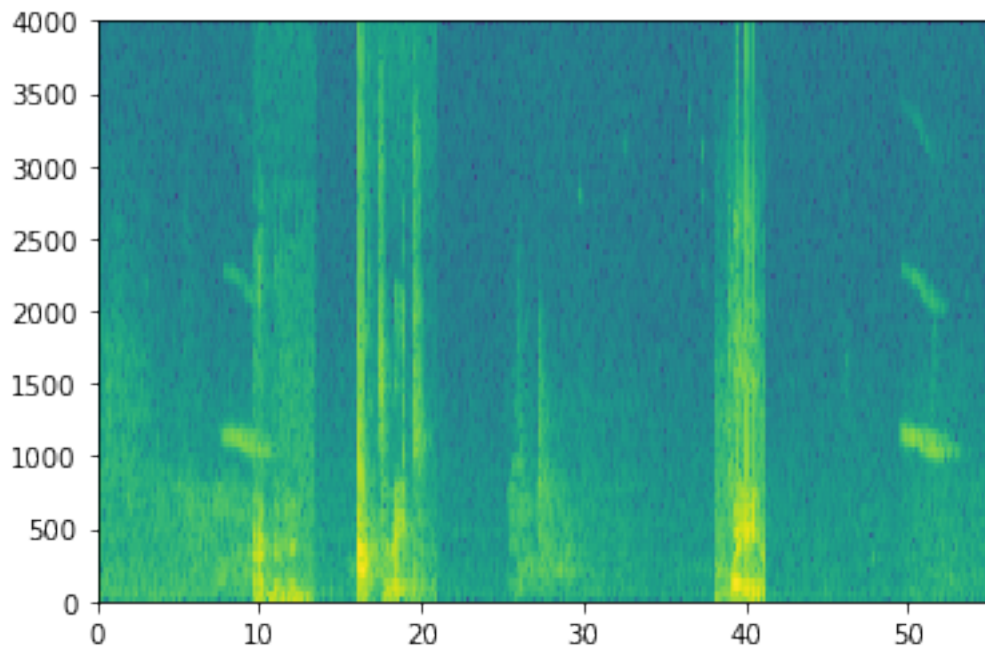
# Get and plot spectrogram of the new recording (background with super
x = graph_spectrogram("train.wav")

return x, y

```

```
In [20]: x, y = create_training_example(backgrounds[0], activates, negatives)
```

File (train.wav) was saved in your directory.



### Expected Output

Now you can listen to the training example you created and compare it to the spectrogram generated above.

```
In [21]: IPython.display.Audio("train.wav")
```

```
Out[21]: <IPython.lib.display.Audio object>
```

### Expected Output

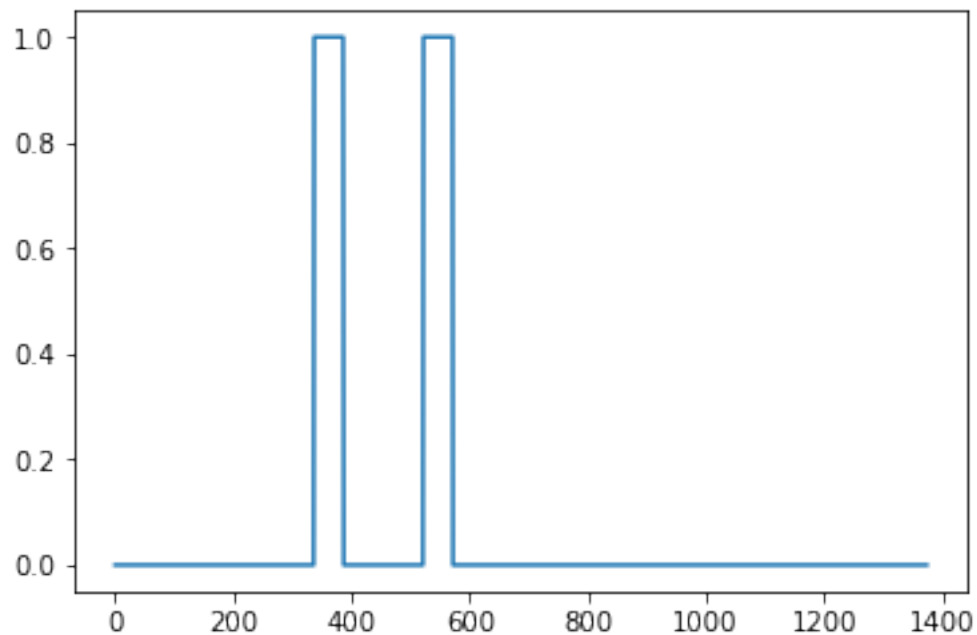
```
In [22]: IPython.display.Audio("audio_examples/train_reference.wav")
```

```
Out [22]: <IPython.lib.display.Audio object>
```

Finally, you can plot the associated labels for the generated training example.

```
In [23]: plt.plot(y[0])
```

```
Out [23]: [<matplotlib.lines.Line2D at 0x7f0794504d30>]
```



### Expected Output

#### 1.4 1.4 - Full training set

- You’ve now implemented the code needed to generate a single training example.
- We used this process to generate a large training set.
- To save time, we’ve already generated a set of training examples.

```
In [24]: # Load preprocessed training examples
         X = np.load("./XY_train/X.npy")
         Y = np.load("./XY_train/Y.npy")
```

#### 1.5 1.5 - Development set

- To test our model, we recorded a development set of 25 examples.
- While our training data is synthesized, we want to create a development set using the same distribution as the real inputs.
- Thus, we recorded 25 10-second audio clips of people saying “activate” and other random words, and labeled them by hand.



- This follows the principle described in Course 3 “Structuring Machine Learning Projects” that we should create the dev set to be as similar as possible to the test set distribution
  - This is why our **dev set uses real audio** rather than synthesized audio.

```
In [25]: # Load preprocessed dev set examples
X_dev = np.load("./XY_dev/X_dev.npy")
Y_dev = np.load("./XY_dev/Y_dev.npy")
```

## 2 2 - Model

- Now that you’ve built a dataset, let’s write and train a trigger word detection model!
- The model will use 1-D convolutional layers, GRU layers, and dense layers.
- Let’s load the packages that will allow you to use these layers in Keras. This might take a minute to load.

```
In [26]: from keras.callbacks import ModelCheckpoint
         from keras.models import Model, load_model, Sequential
         from keras.layers import Dense, Activation, Dropout, Input, Masking, TimeDistributed
         from keras.layers import GRU, Bidirectional, BatchNormalization, Reshape
         from keras.optimizers import Adam
```

Using TensorFlow backend.

### 2.1 2.1 - Build the model

Our goal is to build a network that will ingest a spectrogram and output a signal when it detects the trigger word. This network will use 4 layers: \* A convolutional layer \* Two GRU layers \* A dense layer.

Here is the architecture we will use.

**Figure 3**

**1D convolutional layer** One key layer of this model is the 1D convolutional step (near the bottom of Figure 3). \* It inputs the 5511 step spectrogram. Each step is a vector of 101 units. \* It outputs a 1375 step output \* This output is further processed by multiple layers to get the final  $T_y = 1375$  step output. \* This 1D convolutional layer plays a role similar to the 2D convolutions you saw in Course 4, of extracting low-level features and then possibly generating an output of a smaller dimension. \* Computationally, the 1-D conv layer also helps speed up the model because now the GRU can process only 1375 timesteps rather than 5511 timesteps.

#### GRU, dense and sigmoid

- The two GRU layers read the sequence of inputs from left to right.
- A dense plus sigmoid layer makes a prediction for  $y^{(t)}$ .
- Because  $y$  is a binary value (0 or 1), we use a sigmoid output at the last layer to estimate the chance of the output being 1, corresponding to the user having just said “activate.”

## Unidirectional RNN

- Note that we use a **unidirectional RNN** rather than a bidirectional RNN.
- This is really important for trigger word detection, since we want to be able to detect the trigger word almost immediately after it is said.
- If we used a bidirectional RNN, we would have to wait for the whole 10sec of audio to be recorded before we could tell if “activate” was said in the first second of the audio clip.

**Implement the model** Implementing the model can be done in four steps:

**Step 1:** CONV layer. Use `Conv1D()` to implement this, with 196 filters, a filter size of 15 (`kernel_size=15`), and stride of 4. [conv1d](#)

```
output_x = Conv1D(filters=..., kernel_size=..., strides=...)(input_x)
```

- Follow this with a ReLu activation. Note that we can pass in the name of the desired activation as a string, all in lowercase letters.

```
output_x = Activation("...")(input_x)
```

- Follow this with dropout, using a keep rate of 0.8

```
output_x = Dropout(rate=...)(input_x)
```

**Step 2:** First GRU layer. To generate the GRU layer, use 128 units.

```
output_x = GRU(units=..., return_sequences = ...)(input_x)
```

- Return sequences instead of just the last time step’s prediction to ensures that all the GRU’s hidden states are fed to the next layer.
- Follow this with dropout, using a keep rate of 0.8.
- Follow this with batch normalization. No parameters need to be set.

```
output_x = BatchNormalization()(input_x)
```

**Step 3:** Second GRU layer. This has the same specifications as the first GRU layer. \* Follow this with a dropout, batch normalization, and then another dropout.

**Step 4:** Create a time-distributed dense layer as follows:

```
X = TimeDistributed(Dense(1, activation = "sigmoid"))(X)
```

This creates a dense layer followed by a sigmoid, so that the parameters used for the dense layer are the same for every time step.

Documentation: \* [Keras documentation on wrappers](#).

To learn more, you can read this blog post [How to Use the TimeDistributed Layer in Keras](#).

**Exercise:** Implement `model()`, the architecture is presented in Figure 3.

```
In [27]: # GRADED FUNCTION: model
```

```
def model(input_shape):  
    """  
    Function creating the model's graph in Keras.  
  
    Argument:  
    input_shape -- shape of the model's input data (using Keras convention)  
  
    Returns:  
    model -- Keras model instance  
    """  
  
    X_input = Input(shape = input_shape)  
  
    ### START CODE HERE ###  
  
    # Step 1: CONV layer (~4 lines)  
    X = Conv1D(196, 15, strides=4)(X_input)           # CONV1D  
    X = BatchNormalization()(X)                       # Batch normalization  
    X = Activation('relu')(X)                         # ReLu activation  
    X = Dropout(0.8)(X)                               # dropout (use 0.8)  
  
    # Step 2: First GRU Layer (~4 lines)  
    X = GRU(units = 128, return_sequences=True)(X)   # GRU (use 128 units)  
    X = Dropout(0.8)(X)                               # dropout (use 0.8)  
    X = BatchNormalization()(X)                       # Batch normalization  
  
    # Step 3: Second GRU Layer (~4 lines)  
    X = GRU(units = 128, return_sequences=True)(X)   # GRU (use 128 units)  
    X = Dropout(0.8)(X)                               # dropout (use 0.8)  
    X = BatchNormalization()(X)                       # Batch normalization  
    X = Dropout(0.8)(X)                               # dropout (use 0.8)  
  
    # Step 4: Time-distributed dense layer (see given code in instructions)  
    X = TimeDistributed(Dense(1, activation = "sigmoid"))(X) # time distributed  
  
    ### END CODE HERE ###  
  
    model = Model(inputs = X_input, outputs = X)  
  
    return model
```

```
In [28]: model = model(input_shape = (Tx, n_freq))
```

Let's print the model summary to keep track of the shapes.

```
In [29]: model.summary()
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 5511, 101)	0
conv1d_1 (Conv1D)	(None, 1375, 196)	297136
batch_normalization_1 (Batch Normalization)	(None, 1375, 196)	784
activation_1 (Activation)	(None, 1375, 196)	0
dropout_1 (Dropout)	(None, 1375, 196)	0
gru_1 (GRU)	(None, 1375, 128)	124800
dropout_2 (Dropout)	(None, 1375, 128)	0
batch_normalization_2 (Batch Normalization)	(None, 1375, 128)	512
gru_2 (GRU)	(None, 1375, 128)	98688
dropout_3 (Dropout)	(None, 1375, 128)	0
batch_normalization_3 (Batch Normalization)	(None, 1375, 128)	512
dropout_4 (Dropout)	(None, 1375, 128)	0
time_distributed_1 (TimeDistributed)	(None, 1375, 1)	129
Total params: 522,561		
Trainable params: 521,657		
Non-trainable params: 904		

### Expected Output:

#### Total params

522,561

#### Trainable params

521,657

#### Non-trainable params

904

The output of the network is of shape (None, 1375, 1) while the input is (None, 5511, 101). The Conv1D has reduced the number of steps from 5511 to 1375.

## 2.2 2.2 - Fit the model

- Trigger word detection takes a long time to train.

- To save time, we've already trained a model for about 3 hours on a GPU using the architecture you built above, and a large training set of about 4000 examples.
- Let's load the model.

```
In [30]: model = load_model('./models/tr_model.h5')
```

You can train the model further, using the Adam optimizer and binary cross entropy loss, as follows. This will run quickly because we are training just for one epoch and with a small training set of 26 examples.

```
In [31]: opt = Adam(lr=0.0001, beta_1=0.9, beta_2=0.999, decay=0.01)
         model.compile(loss='binary_crossentropy', optimizer=opt, metrics=["accuracy"])
```

```
In [32]: model.fit(X, Y, batch_size = 5, epochs=1)
```

```
Epoch 1/1
```

```
26/26 [=====] - 39s - loss: 0.0727 - acc: 0.9806
```

```
Out[32]: <keras.callbacks.History at 0x7f060d2f09e8>
```

## 2.3 - Test the model

Finally, let's see how your model performs on the dev set.

```
In [33]: loss, acc = model.evaluate(X_dev, Y_dev)
         print("Dev set accuracy = ", acc)
```

```
25/25 [=====] - 5s
```

```
Dev set accuracy = 0.946036338806
```

This looks pretty good! \* However, accuracy isn't a great metric for this task \* Since the labels are heavily skewed to 0's, a neural network that just outputs 0's would get slightly over 90% accuracy. \* We could define more useful metrics such as F1 score or Precision/Recall. \* Let's not bother with that here, and instead just empirically see how the model does with some predictions.

## 3 - Making Predictions

Now that you have built a working model for trigger word detection, let's use it to make predictions. This code snippet runs audio (saved in a wav file) through the network.

```
In [34]: def detect_triggerword(filename):
         plt.subplot(2, 1, 1)

         x = graph_spectrogram(filename)
         # the spectrogram outputs (freqs, Tx) and we want (Tx, freqs) to input
         x = x.swapaxes(0, 1)
         x = np.expand_dims(x, axis=0)
```

```

predictions = model.predict(x)

plt.subplot(2, 1, 2)
plt.plot(predictions[0, :, 0])
plt.ylabel('probability')
plt.show()
return predictions

```

### Insert a chime to acknowledge the “activate” trigger

- Once you’ve estimated the probability of having detected the word “activate” at each output step, you can trigger a “chiming” sound to play when the probability is above a certain threshold.
- $y^{(t)}$  might be near 1 for many values in a row after “activate” is said, yet we want to chime only once.
  - So we will insert a chime sound at most once every 75 output steps.
  - This will help prevent us from inserting two chimes for a single instance of “activate”.
  - This plays a role similar to non-max suppression from computer vision.

```

In [35]: chime_file = "audio_examples/chime.wav"
def chime_on_activate(filename, predictions, threshold):
    audio_clip = AudioSegment.from_wav(filename)
    chime = AudioSegment.from_wav(chime_file)
    Ty = predictions.shape[1]
    # Step 1: Initialize the number of consecutive output steps to 0
    consecutive_timesteps = 0
    # Step 2: Loop over the output steps in the y
    for i in range(Ty):
        # Step 3: Increment consecutive output steps
        consecutive_timesteps += 1
        # Step 4: If prediction is higher than the threshold and more than
        if predictions[0,i,0] > threshold and consecutive_timesteps > 75:
            # Step 5: Superpose audio and background using pydub
            audio_clip = audio_clip.overlay(chime, position = ((i / Ty) *
            # Step 6: Reset consecutive output steps to 0
            consecutive_timesteps = 0

    audio_clip.export("chime_output.wav", format='wav')

```

### 3.1 3.3 - Test on dev examples

Let’s explore how our model performs on two unseen audio clips from the development set. Lets first listen to the two dev set clips.

```

In [36]: IPython.display.Audio("./raw_data/dev/1.wav")

```

```

Out[36]: <IPython.lib.display.Audio object>

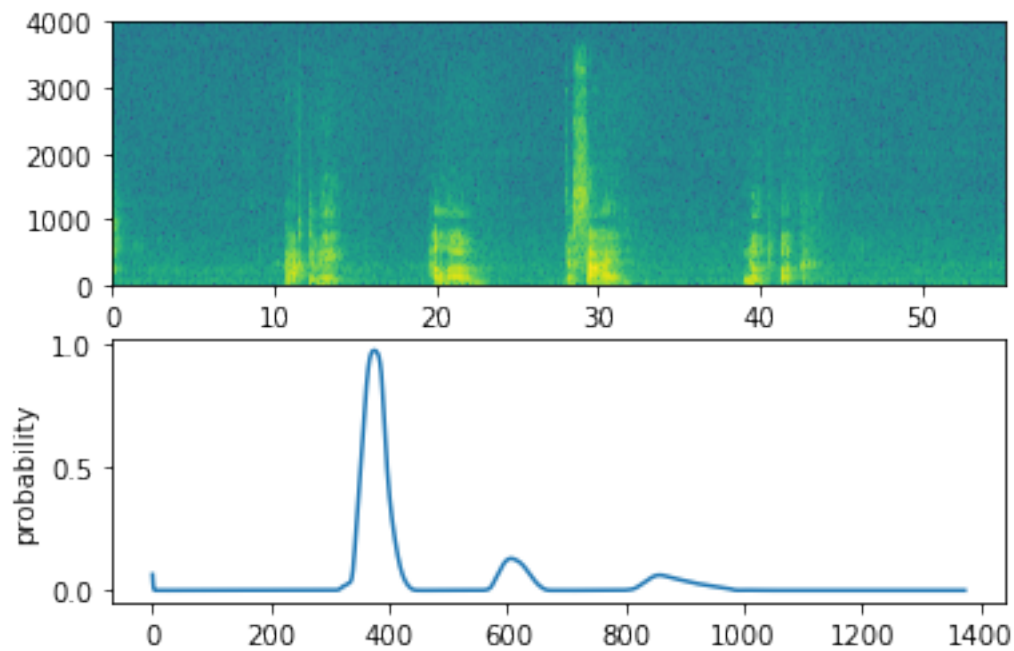
```

```
In [37]: IPython.display.Audio("./raw_data/dev/2.wav")
```

```
Out[37]: <IPython.lib.display.Audio object>
```

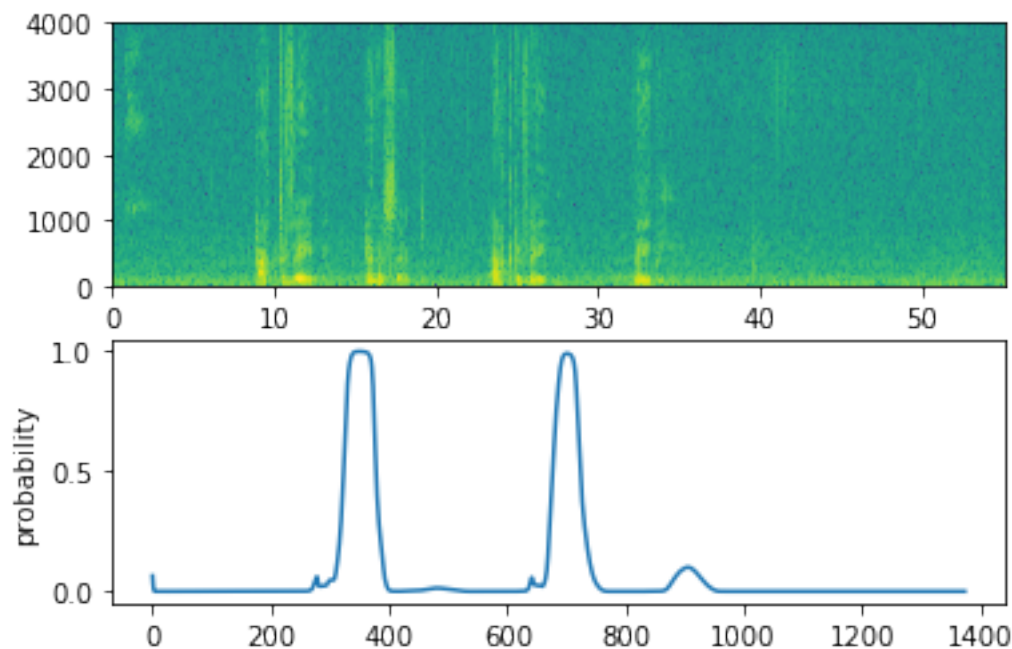
Now lets run the model on these audio clips and see if it adds a chime after “activate”!

```
In [38]: filename = "./raw_data/dev/1.wav"
prediction = detect_triggerword(filename)
chime_on_activate(filename, prediction, 0.5)
IPython.display.Audio("./chime_output.wav")
```



```
Out[38]: <IPython.lib.display.Audio object>
```

```
In [39]: filename = "./raw_data/dev/2.wav"
prediction = detect_triggerword(filename)
chime_on_activate(filename, prediction, 0.5)
IPython.display.Audio("./chime_output.wav")
```



Out [39]: <IPython.lib.display.Audio object>

## 4 Congratulations

You've come to the end of this assignment!

### 4.1 Here's what you should remember:

- Data synthesis is an effective way to create a large training set for speech problems, specifically trigger word detection.
- Using a spectrogram and optionally a 1D conv layer is a common pre-processing step prior to passing audio data to an RNN, GRU or LSTM.
- An end-to-end deep learning approach can be used to build a very effective trigger word detection system.

*Congratulations* on finishing the final assignment!

Thank you for sticking with us through the end and for all the hard work you've put into learning deep learning. We hope you have enjoyed the course!

## 5 4 - Try your own example! (OPTIONAL/UNGRADED)

In this optional and ungraded portion of this notebook, you can try your model on your own audio clips!



- Record a 10 second audio clip of you saying the word “activate” and other random words, and upload it to the Coursera hub as `myaudio.wav`.
- Be sure to upload the audio as a wav file.
- If your audio is recorded in a different format (such as mp3) there is free software that you can find online for converting it to wav.
- If your audio recording is not 10 seconds, the code below will either trim or pad it as needed to make it 10 seconds.

```
In [40]: # Preprocess the audio to the correct format
def preprocess_audio(filename):
    # Trim or pad audio segment to 10000ms
    padding = AudioSegment.silent(duration=10000)
    segment = AudioSegment.from_wav(filename)[:10000]
    segment = padding.overlay(segment)
    # Set frame rate to 44100
    segment = segment.set_frame_rate(44100)
    # Export as wav
    segment.export(filename, format='wav')
```

Once you’ve uploaded your audio file to Coursera, put the path to your file in the variable below.

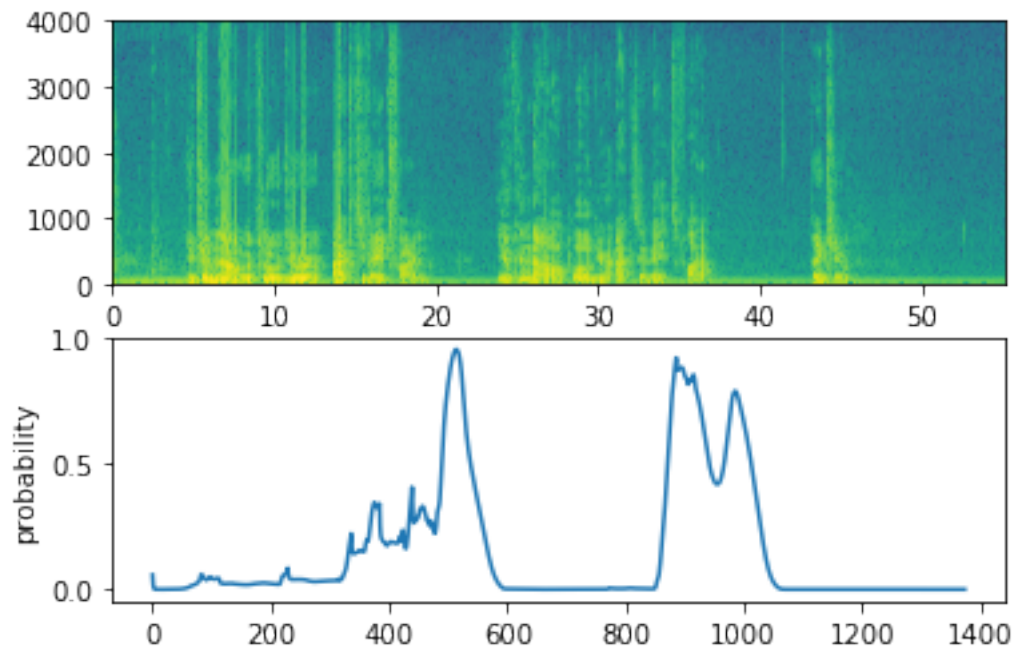
```
In [41]: your_filename = "audio_examples/my_audio.wav"

In [42]: preprocess_audio(your_filename)
IPython.display.Audio(your_filename) # listen to the audio you uploaded

Out[42]: <IPython.lib.display.Audio object>
```

Finally, use the model to predict when you say activate in the 10 second audio clip, and trigger a chime. If beeps are not being added appropriately, try to adjust the `chime_threshold`.

```
In [43]: chime_threshold = 0.5
prediction = detect_triggerword(your_filename)
chime_on_activate(your_filename, prediction, chime_threshold)
IPython.display.Audio("./chime_output.wav")
```



Out[43]: <IPython.lib.display.Audio object>