Assignment 1 - Audio Feature Extraction

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1 Submisson Details

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All the comments are added as Markdown comments and the report is generated by rendering this Jupyter Notebook to a LaTeX project.

The content has been understood from the following resources -

1. Speech and Language Processing by Jurafsky & Martin
2. http://practicalcryptography.com/miscellaneous/machine-learning/guide-mel-frequency-cepstral-coefficients-mfccs/
3. https://medium.com/@jonathan_hui/speech-recognition-feature-extraction-mfcc-plp-5455f5a69dd9
4. TA

```
In [1]: import librosa
        import numpy as np
        import scipy as sp
        import matplotlib.pyplot as plt
        import librosa.display as ld

        import IPython.display as ipd
```

1.0.1 The Audio I recorded says - He is a boy.

```
In [2]: xn, sr = librosa.load('recordings/recording1.wav')
```

```
In [3]: xn.shape
```

```
Out[3]: (104429,)
```

```
In [4]: sr
```

```
Out[4]: 22050
```

2 Annotations

All of the following annotations are in seconds

1. 0.6-0.9 - h (unvoiced phoneme)
2. 0.9-1.4 - ee
3. 1.8-2.4 - i
4. 2.4-2.6 - z (voiced phoneme)
5. 2.9-3.4 - a
6. 3.6-4 - b (voiced phoneme)
7. 4-4.3 - au
8. 4.3-4.5 - ae

```
In [5]: ipd.Audio('recordings/recording1.wav')
```

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

3 1. To Analyse the Sound Spectrogram

3.0.1 a. Custom DFT and STFT

In the following code, I will demonstrate that the spectrogram obtained from my DFT + STFT implementations looks similar to that by library implementations of FFT and STFT with the same parameters

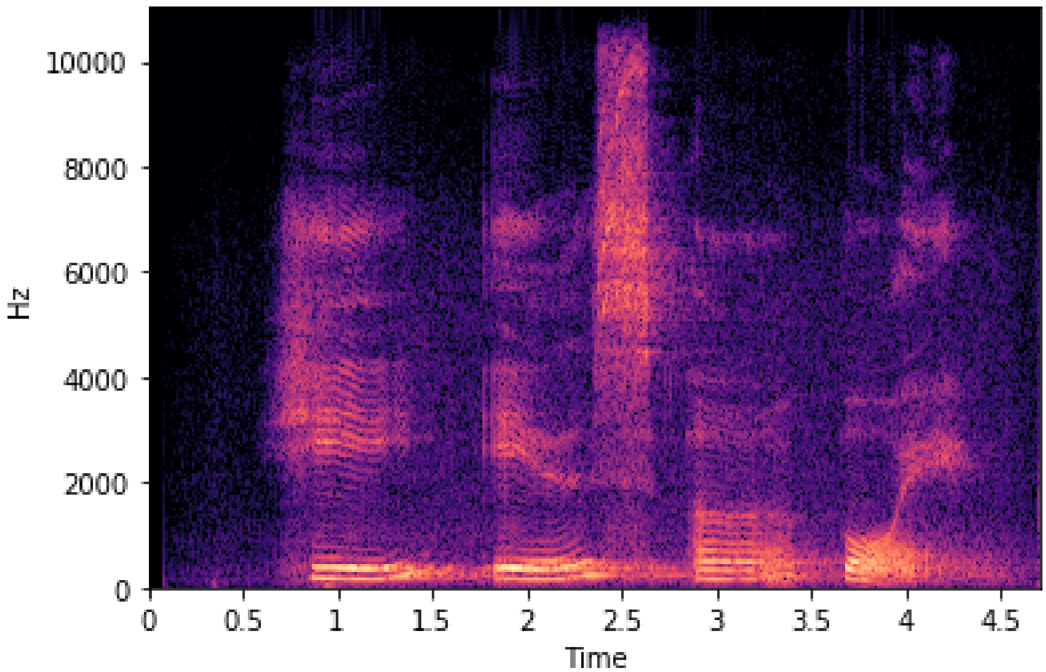
```
In [6]: def dft_custom(xn):
            N = xn.shape[0]
            e_matrix = np.fromfunction(lambda m, n: np.exp(-(2*np.pi*m*n*1j)/N), (N, N))
            return e_matrix.dot(xn)
```

```
In [7]: def stft(xn, window_size = None, hopsize= 512, window = 'hamming', fft_size = 512):
            total_samples = xn.shape[0]

            if window_size == None:
                window_size = fft_size

            if hopsize == None:
                hopsize = int(fft_size/4)


            # Getting window of size window_size
            window_fn = sp.signal.get_window(window, Nx=fft_size)

            start_index = 0 - hopsize
            end_index = window_size - hopsize

            stft_res = []
```

```python
        counter = 0
        while start_index + hopsize <= total_samples - window_size:
            start_index = start_index + hopsize
            end_index = end_index + hopsize

            x_window = xn[start_index:end_index]


            # x_window is of window_size. Need to pad it to fft_size
            diff = fft_size - window_size

            if diff %2==0:

                x_window = np.pad(x_window, (int(diff/2), (int(diff/2))))

            else:

                x_window = np.pad(x_window, (int(diff/2), (int(diff/2)+1)))


            try:

                mult_window = x_window * window_fn

            except:
                print(start_index)
                print(end_index)

            dft_window = dft_custom(mult_window)[:int(fft_size/2)+1]

            stft_res.append(dft_window)

#             print(counter)
            counter+=1

        return np.array(stft_res)
```

```python
In [8]: res = stft(xn,window_size =500, hopsize = int(500/4))
```

```python
In [9]: ld.specshow(librosa.amplitude_to_db(np.abs(res.T),ref=np.max), hop_length=int(500/4),y_a
        plt.savefig('my_stft_dft_recording1.png')
```




```
In [10]: res.shape
```

```
Out[10]: (832, 257)
```

In the spectrogram above, while keeping the annotations in mind, the following things are observed:

1. Vowels have a large number of (high amplitude) low frequencies, making them visually distinguishable
2. Voiced phonemes like 'z' and 'b' have a **range** of frequencies, which makes them distinguishable. Viewing them in the spectrogram demonstrates that too.
3. Unvoiced phonemes like 'h' are difficult to distinguish in the spectrogram (the results for which can also be observed in the clustering experiment below)

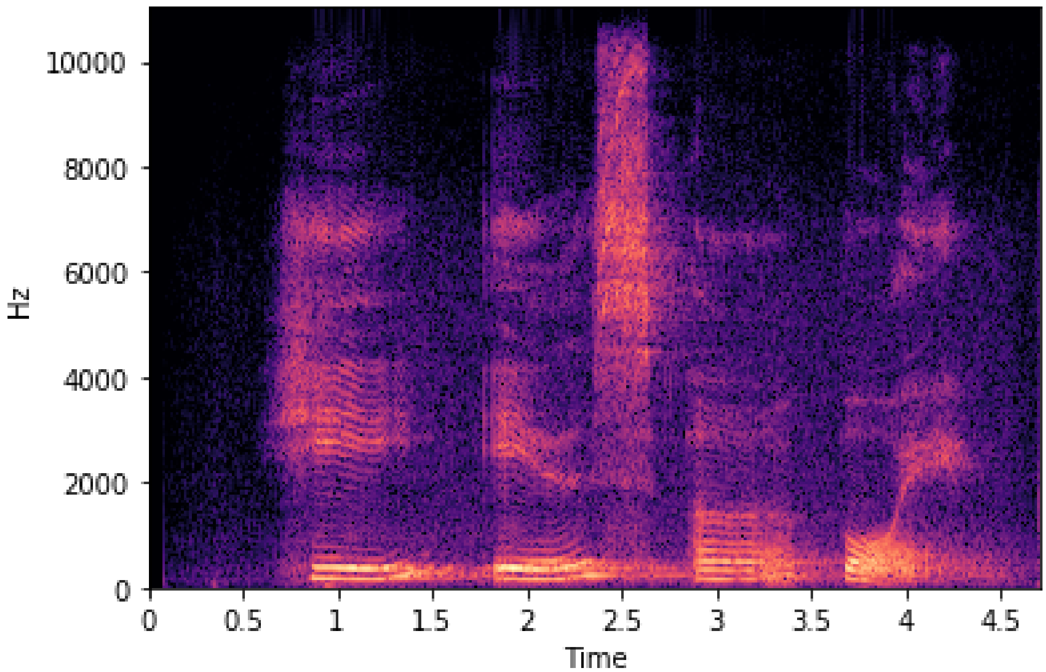
3.0.2 b. FFT with STFT

```
In [11]: def stft_fft(xn, window_size = None, hopsize= 512, window = 'hamming', fft_size = 512):
             total_samples = xn.shape[0]

             if window_size == None:
                 window_size = fft_size

             if hopsize == None:
                 hopsize = int(fft_size/4)
```

```python
    # Getting window of size window_size
    window_fn = sp.signal.get_window(window, Nx=fft_size)

    start_index = 0 - hopsize
    end_index = window_size - hopsize

    stft_res = []


    counter = 0
    while start_index + hopsize <= total_samples - window_size:
        start_index = start_index + hopsize
        end_index = end_index + hopsize

        x_window = xn[start_index:end_index]


        # x_window is of window_size. Need to pad it to fft_size
        diff = fft_size - window_size

        if diff %2==0:

            x_window = np.pad(x_window, (int(diff/2), (int(diff/2))))

        else:

            x_window = np.pad(x_window, (int(diff/2), (int(diff/2)+1)))


        try:

            mult_window = x_window * window_fn

        except:
            print(start_index)
            print(end_index)

        dft_window = np.fft.fft(mult_window)[:int(fft_size/2)+1]

        stft_res.append(dft_window)

#           print(counter)
        counter+=1

    return np.array(stft_res)
```

In [12]: res_stft = stft_fft(xn,window_size =500, hopsize = int(500/4))

In [13]: ld.specshow(librosa.amplitude_to_db(np.abs(res_stft.T),ref=np.max), hop_length=int(500/
plt.savefig('my_stft_fft_recording1.png')



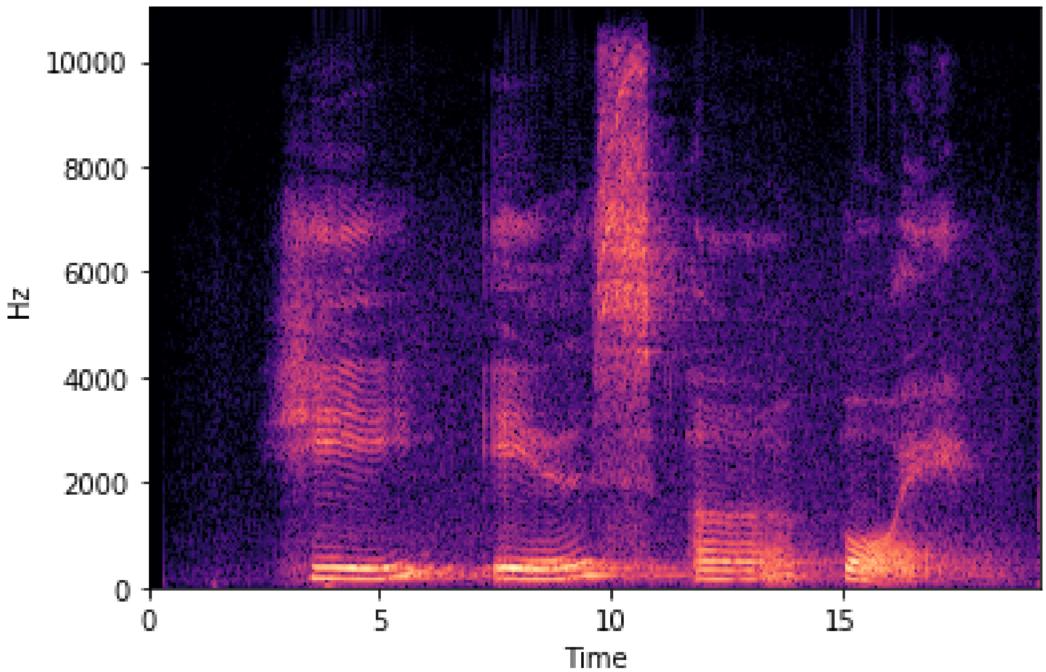
In [14]: res_stft.shape

Out[14]: (832, 257)

3.0.3 c. Librosa Implementation

In [15]: D_short = np.abs(librosa.stft(xn, hop_length=int(500/4), window='hamming', n_fft=512, w

In [16]: ld.specshow(librosa.amplitude_to_db(D_short,ref=np.max), y_axis='linear', x_axis='time'
plt.savefig('librosa_stft_recording1.png')




```
In [17]: D_short.shape
```

```
Out[17]: (257, 832)
```

4 2. MFCC

```
In [18]: def preemphasis(xn, alpha = 0.97):
             # Using pre-empaphases with a certain alpha
             pre_e_xn = np.zeros((xn.shape))

             pre_e_xn[0] = xn[0]

             pre_e_xn[1:] = xn[1:] - alpha * xn[:-1]

             return pre_e_xn
```

```
In [19]: def get_mel_from_hertz(hertz):
             return 2595 * np.log10(1 + (hertz/ 700))
```

```
In [20]: def get_hertz_from_mel(mel):
             return 700 * (10**(mel / 2595) - 1)
```

```
In [21]: def get_power_spectrum(xn_mag, fft_size=2048):
             return (1/fft_size) * np.power(xn_mag, 2)
```

In [22]:
```
def get_triangle_function(prev_freq, cur_freq, nex_freq, filter_banks, bin_fb):

    # Ascending Triangle

    for freq in range(int(prev_freq), int(cur_freq)):

        filter_banks[bin_fb-1,freq] = (freq - prev_freq)/(cur_freq-prev_freq)

    # Descending Triangle

    for freq in range(int(cur_freq+1), int(nex_freq)):

        filter_banks[bin_fb-1, freq] = (nex_freq-freq)/(nex_freq-cur_freq)

    # Triangle Tip

    filter_banks[bin_fb-1, int(cur_freq)] = 1

    return filter_banks
```

In [23]:
```
def mel_filter_banks(xn_pow, sr, number_filters, fft_size=2048):
    min_mel = 0
    max_mel = get_mel_from_hertz(sr/2)

    mel_freq_points = np.linspace(min_mel, max_mel, num=number_filters+2)
    hertz_freq_points = get_hertz_from_mel(mel_freq_points)

    corresponding_bins_hertz_points = np.floor((fft_size + 1) * hertz_freq_points / sr)

    # Filter banks have to be of shape number_filters * (fft_size/2) + 1
    filter_banks = np.zeros((number_filters, int(fft_size/2)+1))

    for bin_fb in range(1, number_filters+1):

        prev_bin = corresponding_bins_hertz_points[bin_fb-1]
        current_bin = corresponding_bins_hertz_points[bin_fb]
        next_bin = corresponding_bins_hertz_points[bin_fb+1]

        # Use the triangle function to get the values of the banks

        filter_banks = get_triangle_function(prev_bin, current_bin, next_bin, filter_ba

    return filter_banks
```

In [24]:
```
def get_delta_values(x):
    delta_x = np.zeros(shape=x.shape)
```

```
        for i in range(1,x.shape[1]-1):
            prev_val = x[:,i-1]
            next_val = x[:,i+1]

            delta_x[:,i]  = (next_val - prev_val)/2

        return delta_x
```

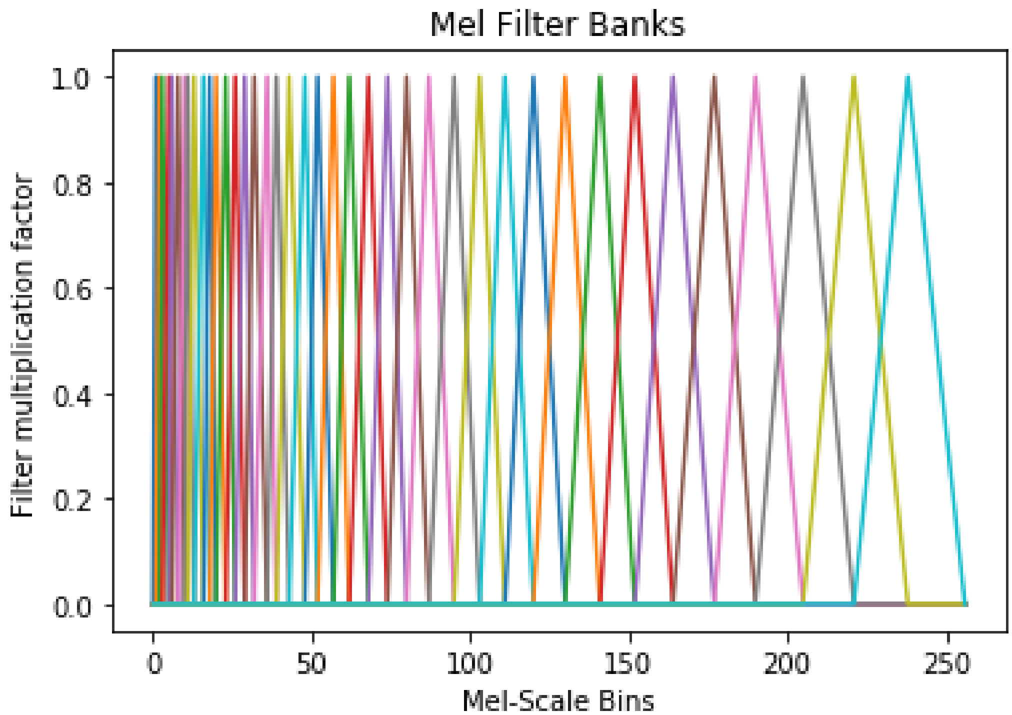
```
In [25]: def mfcc(xn, sr, number_filters, window_size = 500, hopsize=int(500/4), fft_size=512):

        # Pre-emphasis

        xn = preemphasis(xn)

        # Getting the STFT

        xn_stft = stft(xn, window_size= window_size, hopsize=hopsize, fft_size=fft_size)

        # Getting the Magnitude of the STFT

        xn_mag = np.abs(xn_stft)

        # Evaluating the Power spectrum for the magnitude

        xn_pow = get_power_spectrum(xn_mag, fft_size=fft_size)

        # To get the mel filter banks

        filter_banks = mel_filter_banks(xn_pow, sr, number_filters, fft_size=fft_size)

        machine_epsilon =  2.22044604925e-16

        filter_banks[filter_banks==0] = machine_epsilon


        # Multiply the filter_banks with the power spectrum

        filter_banks_res = np.dot(filter_banks, xn_pow.T)

        # Taking the log and the inverse DFT

        filter_banks_res = filter_banks_res + machine_epsilon

        log_filter_bank = np.log(filter_banks_res)

        idft = sp.fftpack.dct(log_filter_bank)

        # First 12 MFCC Values
```

```
    first_12 = idft[:12,:]

    # delta and delta-delta coefficients

    delta = get_delta_values(idft)

    delta_delta = get_delta_values(delta)

    # Getting Energy values of delta and delta-delta coefficients

    first_12_delta = delta[:12,:]

    first_12_delta_delta = delta_delta[:12,:]


    # Energy of the Cepstrum frame. Read from - http://citeseerx.ist.psu.edu/viewdoc/do

    energy = np.sqrt(np.sum(np.power(first_12,2),axis=0)).reshape(1,-1)

    energy_delta = np.sqrt(np.sum(np.power(first_12_delta,2),axis=0)).reshape(1,-1)

    energy_delta_delta = np.sqrt(np.sum(np.power(first_12_delta_delta,2),axis=0)).resha

    return np.vstack((energy, energy_delta, energy_delta_delta, first_12, first_12_delt
```

```
In [26]: mfcc_xn, filter_banks = mfcc(xn, sr, 40)
```

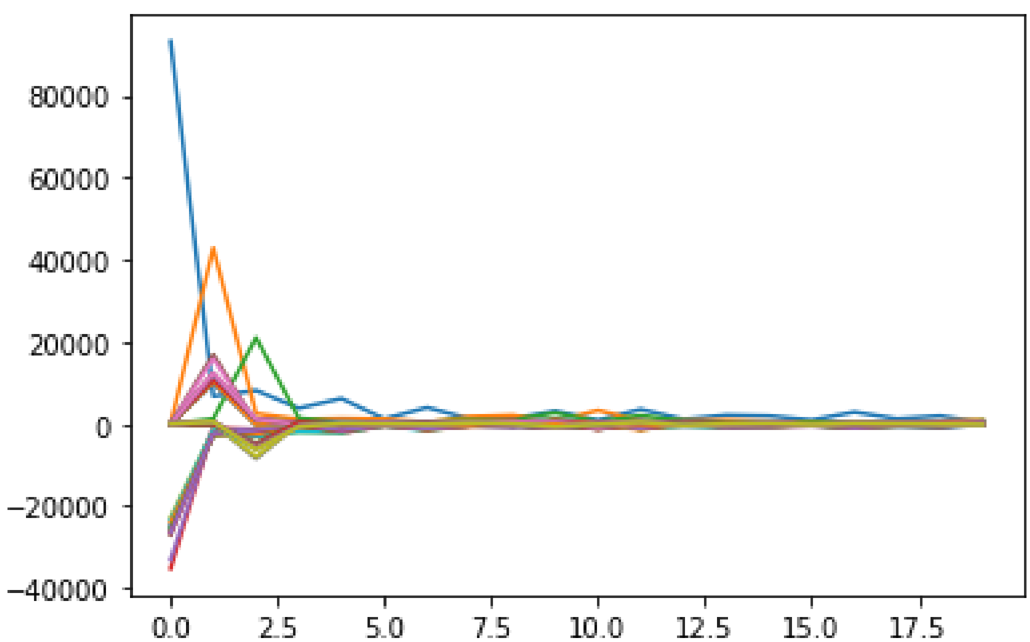
The Implemented Mel Filterbanks look like the following

```
In [27]: plt.plot(filter_banks.T)
         plt.ylabel("Filter multiplication factor")
         plt.xlabel("Mel-Scale Bins")
         plt.title("Mel Filter Banks")
         plt.savefig("mel_filter_banks.png")
         plt.show()
```



Looking at the Cepstral Coefficients, We can see the a small peak is being formed at around the **16th** sample. This shows that the F0 is present athere who's amplitude is around 5000. For ASR Purposes, we only take the first 12 cepstral coefficients

```
In [28]: plt.plot(mfcc_xn.T[:20])
         plt.show()
```



5 3. Clustering

In this experiment, I have conducted the following steps -

1. Spoken 2 examples of vowels and consonants each
2. Taken out MFCC Features of the 4 sound samples

Reading the vowels

```
In [29]: aa, sr = librosa.load('consonants_vowels/Aa.wav')
```

```
In [30]: ee, sr = librosa.load('consonants_vowels/Ee.wav')
```

Reading the consonants

```
In [31]: r, sr = librosa.load('consonants_vowels/R.wav')
```

```
In [32]: sh, sr = librosa.load('consonants_vowels/Sh.wav')
```

5.0.1 Calculating MFCC features of the consonants and vowels

```
In [33]: aa_mfcc = mfcc(aa, sr, 40)[0]

         ee_mfcc = mfcc(ee, sr, 40)[0]

         r_mfcc = mfcc(r, sr, 40)[0]

         sh_mfcc = mfcc(sh, sr, 40)[0]
```

```
In [34]: def get_avg_mfcc(mfcc_vector):
             return np.mean(mfcc_vector, axis=1)
```

```
In [35]: aa_mfcc = get_avg_mfcc(aa_mfcc)
         ee_mfcc = get_avg_mfcc(ee_mfcc)
         r_mfcc = get_avg_mfcc(r_mfcc)
         sh_mfcc = get_avg_mfcc(sh_mfcc)
```

```
In [36]: features = np.vstack((aa_mfcc, ee_mfcc, r_mfcc, sh_mfcc))
```

```
In [37]: features.shape
```

```
Out[37]: (4, 39)
```

Running K Means clustering over the consonant and vowels

```
In [38]: from sklearn.cluster import KMeans
```

```
In [39]: kmeans = KMeans(n_clusters=2, random_state=0).fit(features)
```

```
In [40]: kmeans.labels_
```

```
Out[40]: array([0, 0, 0, 1], dtype=int32)
```

These labels imply that aa, ee, and r are in the same cluster, but sh is not in the same cluster

5.1 Analysis

The experimentation done above was done for 4 different vowels and 5 different consonants. A repeated pattern that was observed was that -

All Vowels were in the same cluster, but all consonants were never clustered together. This can be because *within consonants*, the pronounciation differs for a lot of the consonants (voiced, unvoiced, and other distinctions), making the MFCC features robust enough to understand these features.