

# DSP Lecture 5

## Speech Signal Processing

# Lecture Overview

1. FIR & IIR Filters
2. Classification of Signals
3. Energy / RMS calculation

# Lecture Goals

1. Learn basic concepts about audio processing
2. Learn basic concepts about speech signal processing

# Lecture Overview

1. **FIR & IIR Filters**
2. Classification of Signals
3. Energy / RMS calculation

# FIR & IIR Filters: FIR

**Differential equation:**  $y[n] = b_0x[n] + b_1x[n - 1] + b_2x[n - 2] + \dots + b_Nx[n - N]$

**Transfer function (Z):**  $H(Z) = \frac{B(Z)}{Z^n} = b_0 + b_1Z^{-1} + b_2Z^{-2} + \dots + b_NZ^{-N}$

**Impulse response:**  $h[0] = b_0, h[1] = b_1, h[2] = b_2, \dots, h[N] = b_N, h[N + 1] = 0, \dots$

- **Finite Impulse Response -  $h[n]$  is finite**
- **FIR filters are always stable (by definition- all poles are at the origin,  $z=0$ )**
- **Also known as ‘moving average filters’ (MA), or ‘all zeros’ filters**
- **Pros:**
  - **Stable**
  - **Linear phase**
  - **Easy to implement and construct using closed-form formulas**
- **Cons:**
  - **In order to get a sharp response, large order is required.**
  - **Larger delay compared to IIR**

# FIR & IIR Filters: IIR

**Differential equation:**  $y[n] + a_1y[n-1] + \dots + a_Ny[n-N] = b_0x[n] + b_1x[n-1] + \dots + b_Nx[n-N]$

**Transfer function (Z):**  $H(Z) = \frac{B(Z)}{A(Z)} = \frac{b_0 + b_1Z^{-1} + b_2Z^{-2} + \dots + b_NZ^{-N}}{1 + a_1Z^{-1} + a_2Z^{-2} + \dots + a_NZ^{-N}}$

**Differential equation:**  $y[n] = \underbrace{b_0x[n] + b_1x[n-1] + \dots + b_Nx[n-N]}_{\text{'MA'}}$   $\underbrace{- a_1y[n-1] - a_2y[n-2] - \dots - a_Ny[n-N]}_{\text{'AR'}}$

- **Infinite Impulse Response -  $h[n]$  is infinite**
- **IIR filters iff all poles lie inside the unit circle**
- **Also known as 'AutoRegressive Moving Average filters' (ARMA)**
- **Pros:**
  - **Obtain sharper frequency response compared to same-order FIR filters (by moving the poles from origin)- lower computational complexity**
  - **Lower latency compared to FIR**
- **Cons:**
  - **May cause phase issues**
  - **Harder to implement (no-close form in some cases).**
  - **Overflow may be an issue due to recursiveness (infinite) of the response.**

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1. FIR & IIR Filters
2. **Classification of Signals**
3. Energy / RMS calculation

# Classification of Signals

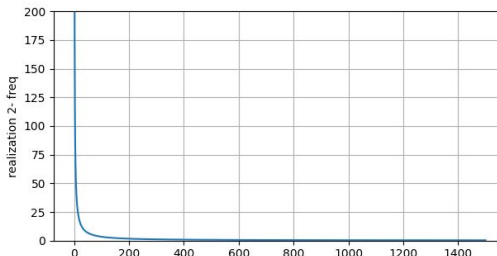
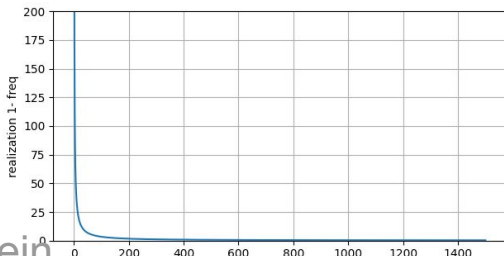
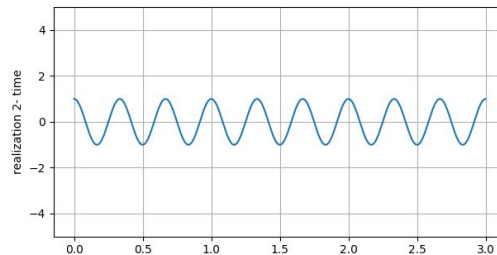
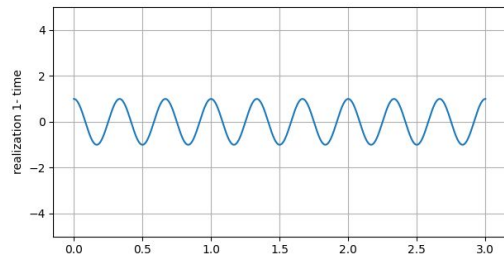
**Signals** can be **classified** in various ways as we saw in previous lectures:

- Continuous vs discrete
- Periodic vs Aperiodic

We will now discuss on two classes:

- Probabilistic Vs Deterministic.

samples1: mean 0.00, std 0.71  
samples2: mean 0.00, std 0.71





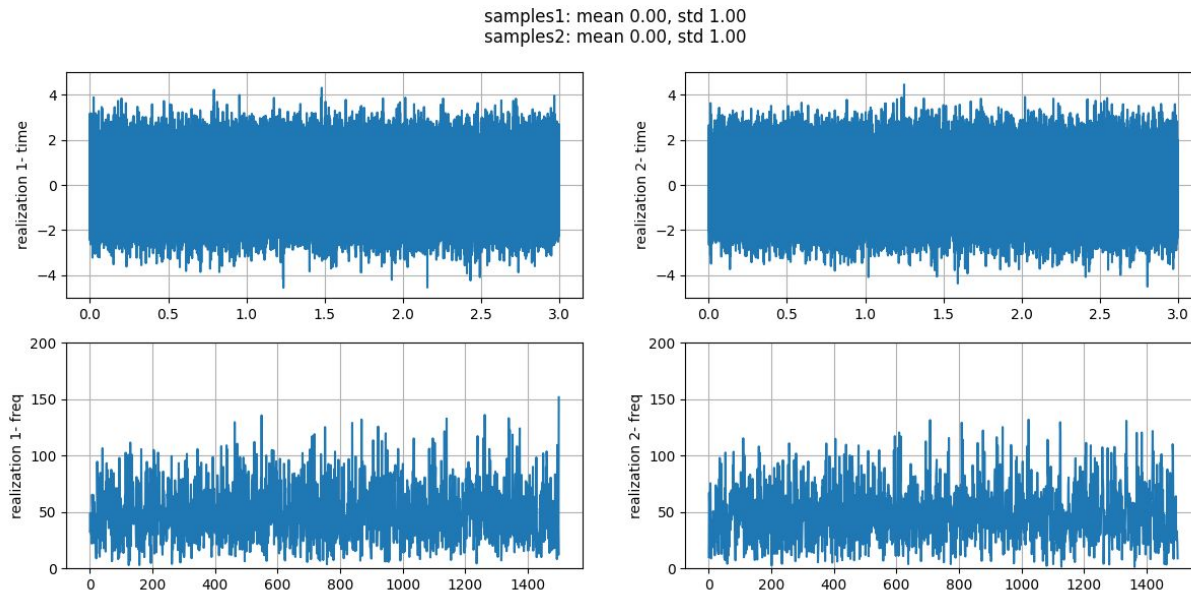
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- Stationary Vs. non-stationary.

**Stationarity** is a way of **describing the characteristics of the signal generating process**, which further gives us two categories.

The difference between **stationary and non-stationary signals** is that the **statistical** (joint probability distribution) **properties of a stationary process signal do not change with time**. Consequently, parameters such as **mean and variance also do not change over time**.

So, a **continuous time random process**  $\{X_t\}$  which is WSS has the following restrictions on its mean function  $m_X(t) \triangleq E[X_t]$  and **autocovariance** function  $K_{XX}(t_1, t_2) \triangleq E[(X_{t_1} - m_X(t_1))(X_{t_2} - m_X(t_2))]$ :

$$\begin{aligned} m_X(t) &= m_X(t + \tau) && \text{for all } \tau \in \mathbb{R} \\ K_{XX}(t_1, t_2) &= K_{XX}(t_1 - t_2, 0) && \text{for all } t_1, t_2 \in \mathbb{R} \quad (\text{Eq.3}) \\ E[|X(t)|^2] &< \infty && \text{for all } t \in \mathbb{R} \end{aligned}$$

# Signals

Stationary:

- White noise (probabilistic & stationary)
- Sin / cos (deterministic & stationary)

Non-Stationary:

- Speech (probabilistic & non-stationary)

Parameter of Comparison	Stationary Signals	Non-Stationary
Time	The time period for the stationary signal remains constant at all times.	The time period for a non-stationary signal varies with time and is not constant.
Frequency	The frequency of a stationary signal remains constant across the process	The frequency of a Non-stationary wave changes constantly during the process.
Spectral Contents	Spectral content for Stationary signals are constant	Spectral contents are dynamic and keep changing in case of the non-stationary signal.
Fourier Equation	Fourier transform is good at representing stationary signals	Fourier transform is non-good at representing non-stationary signals.
Examples	Single-tone sinewave constant frequency, Multitone sine wave of constant frequency	Speech signals, Multitone sinewave of varied frequency

# Classification of Signals

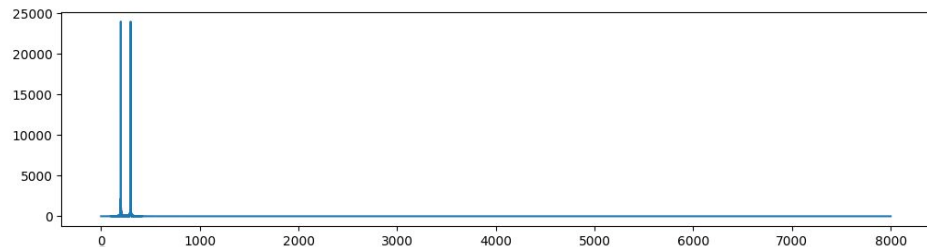
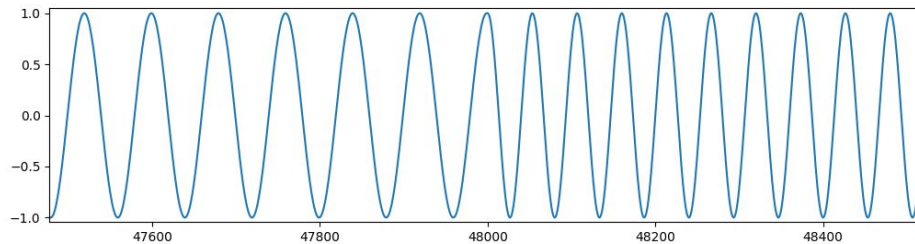
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$\cos 200\text{Hz}$  [0, 48K],  $\cos 300\text{Hz}$  (48K, 96K]



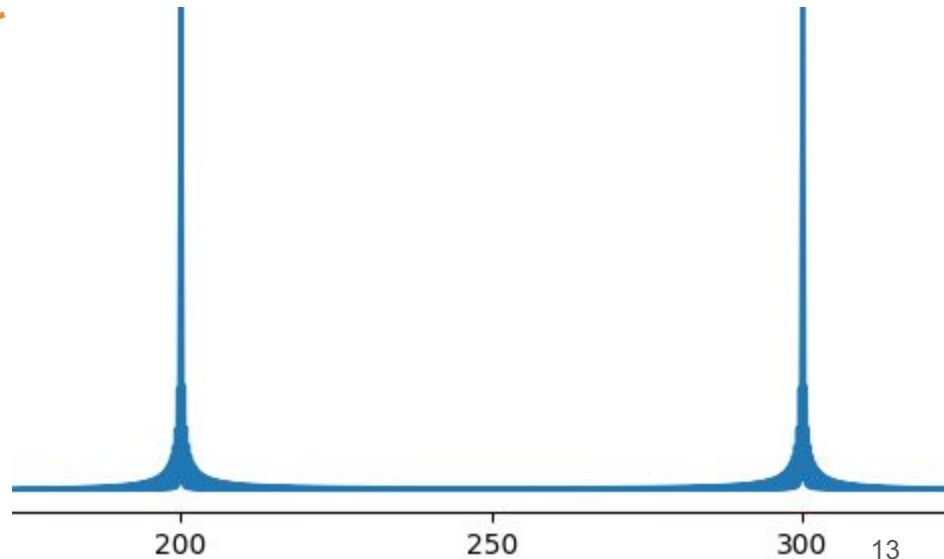
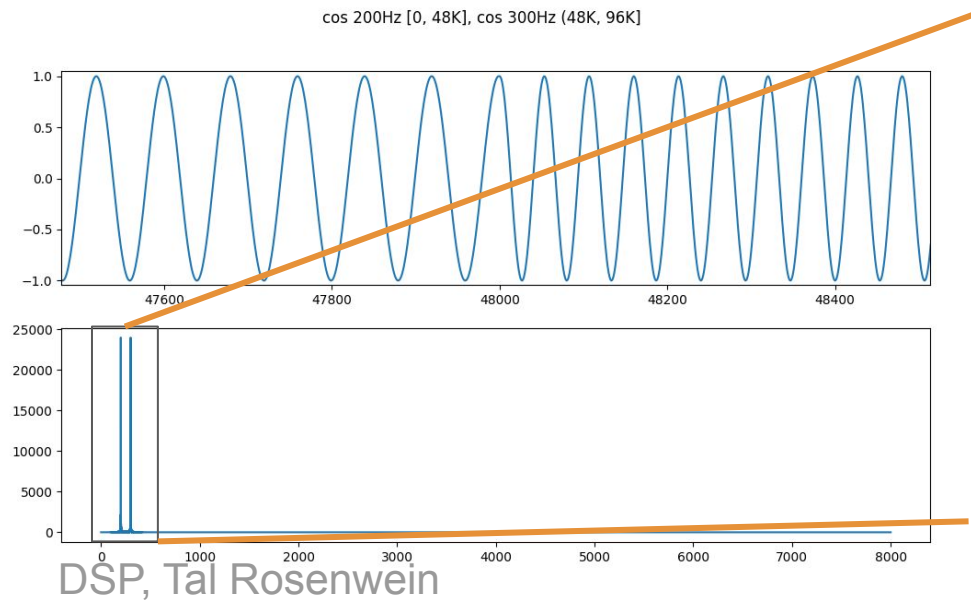
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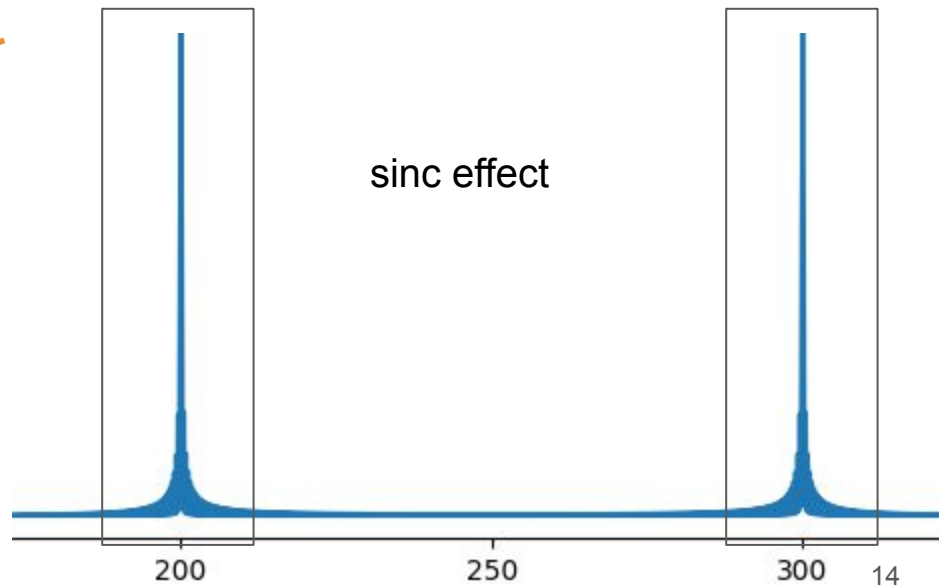
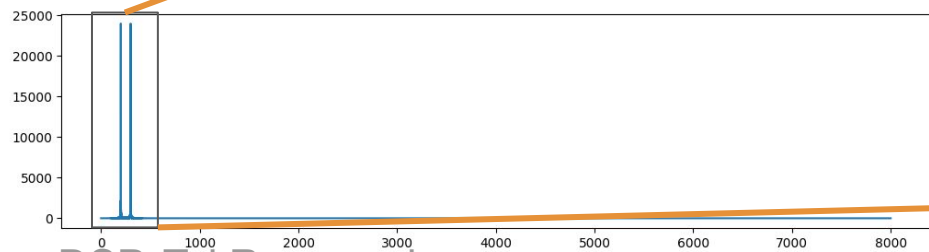
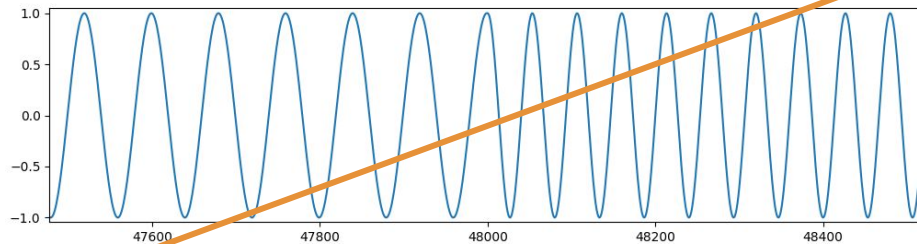
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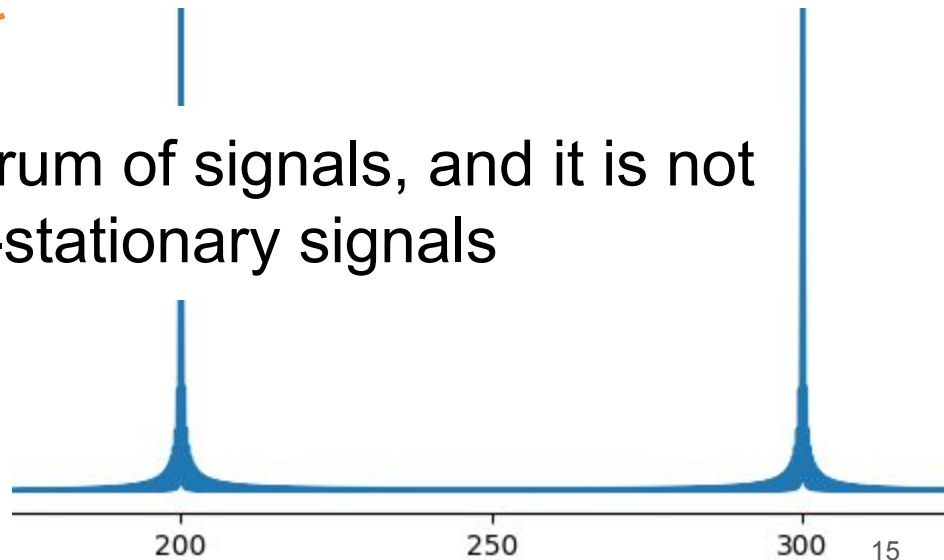
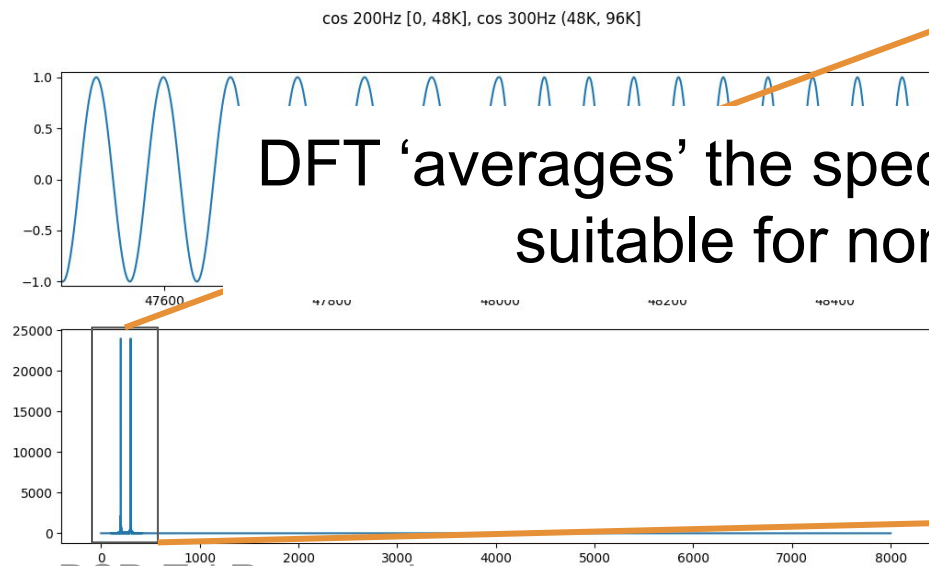
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DFT 'averages' the spectrum of signals, and it is not suitable for non-stationary signals



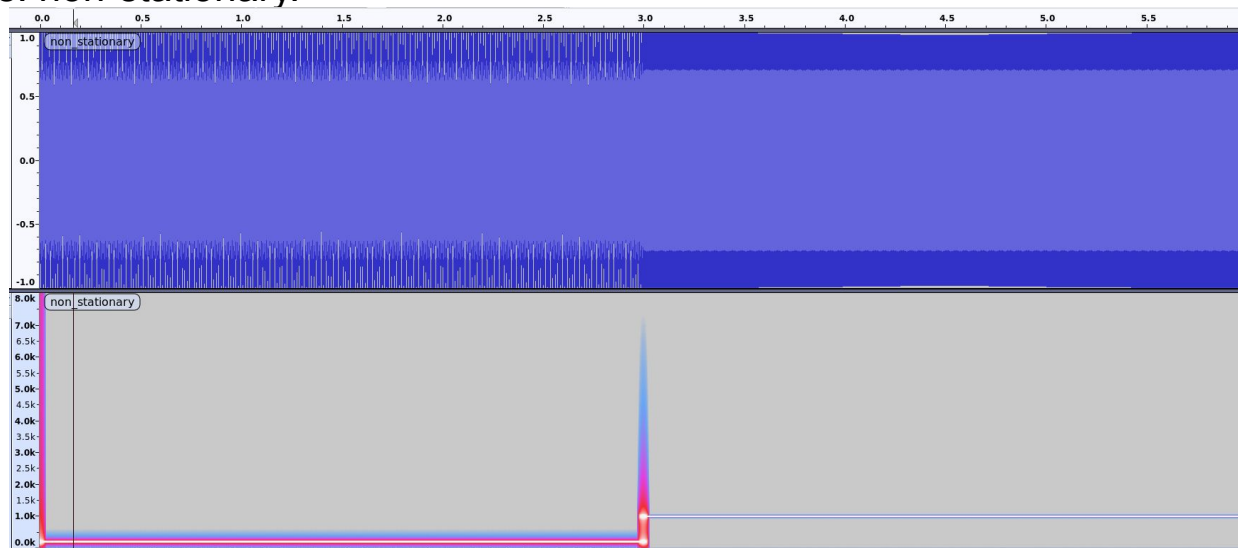
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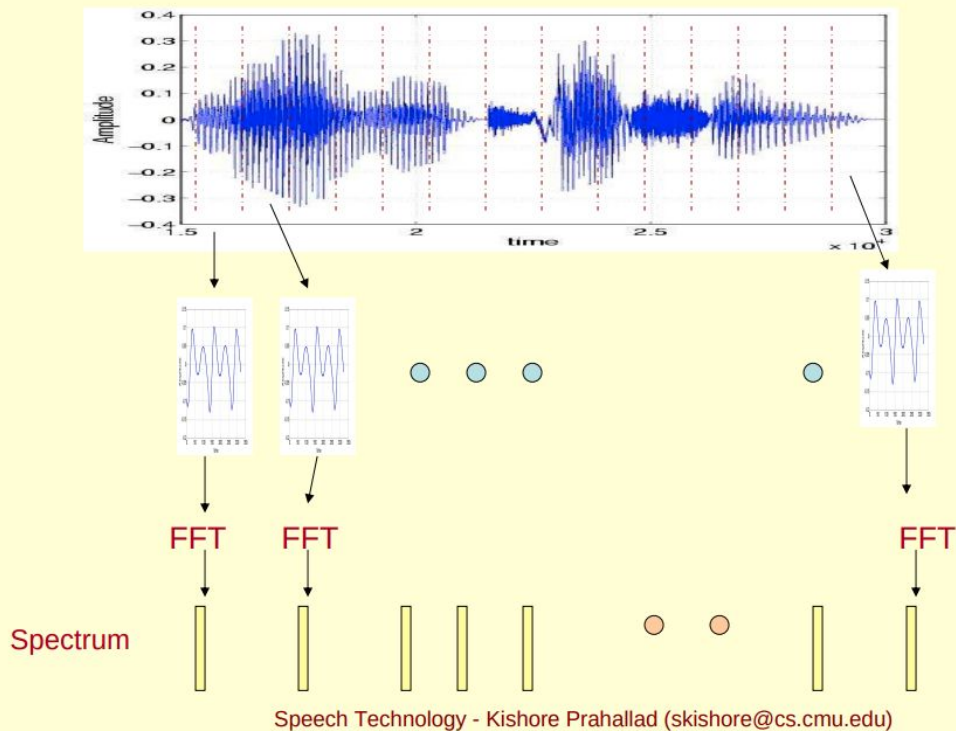
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# Classification of Signals

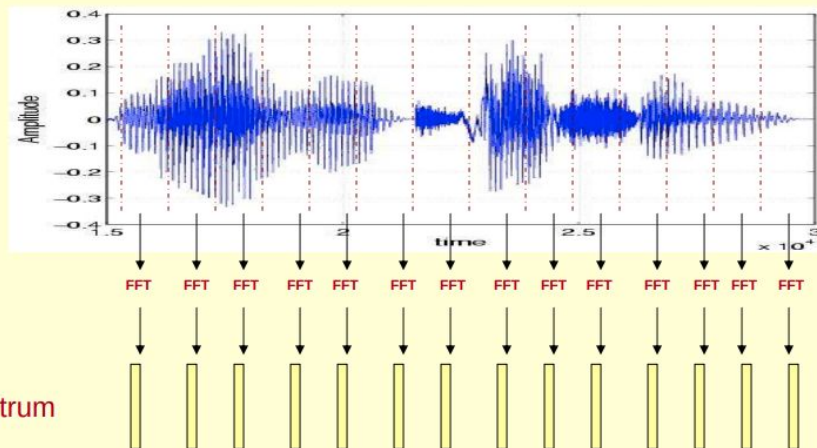
Speech signal represented as a sequence of spectral vectors



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# Classification of Signals

Speech signal represented as a sequence of spectral vectors

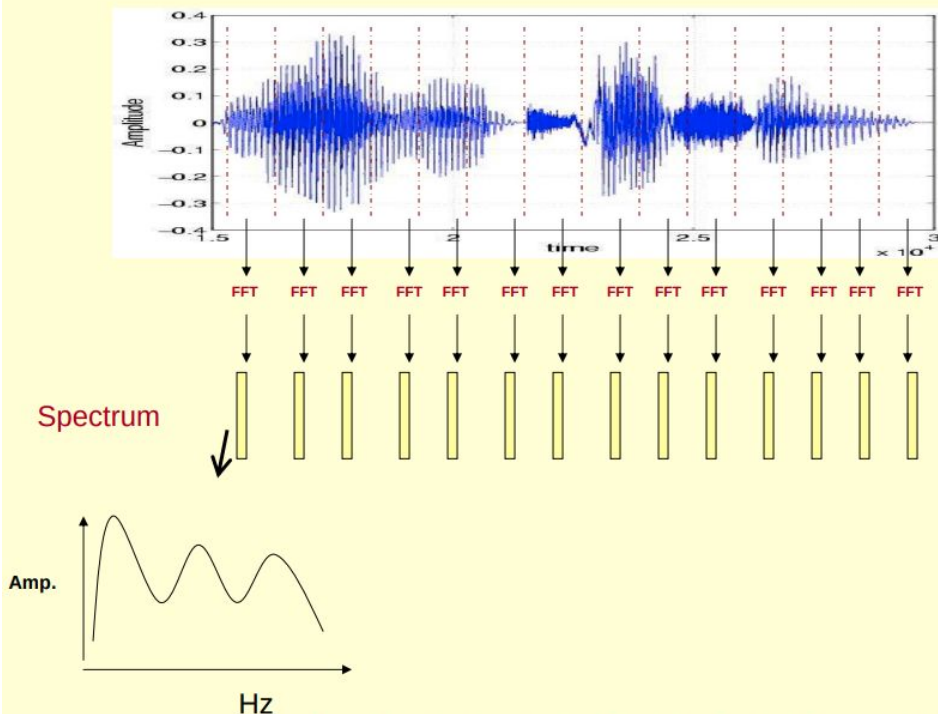


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# Classification of Signals

Speech signal represented as a sequence of spectral vectors

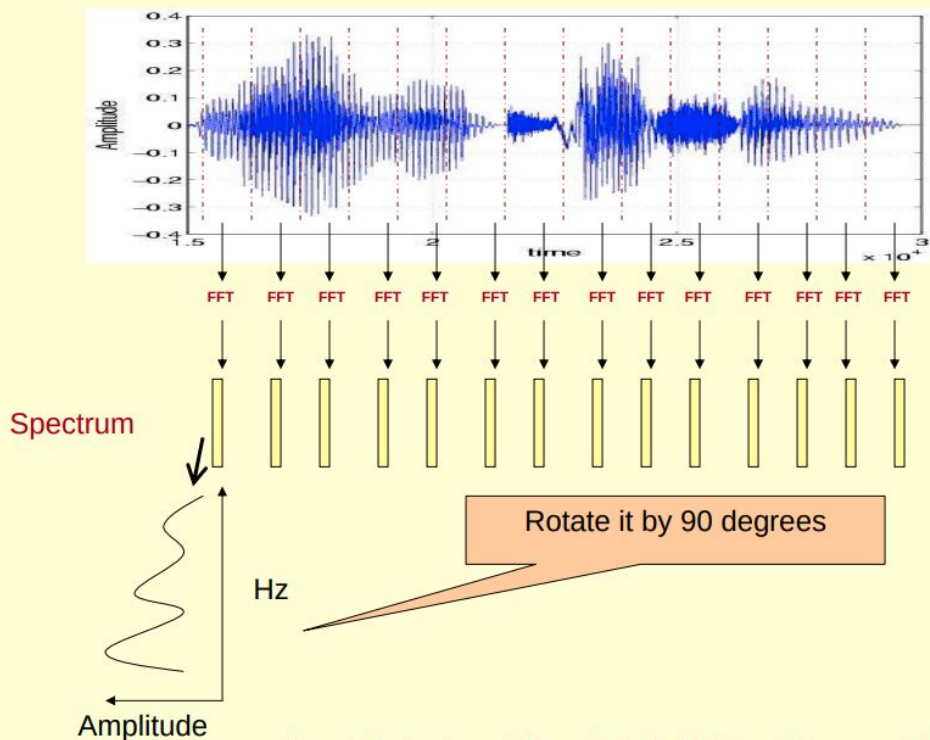


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Speech signal represented as a sequence of spectral vectors

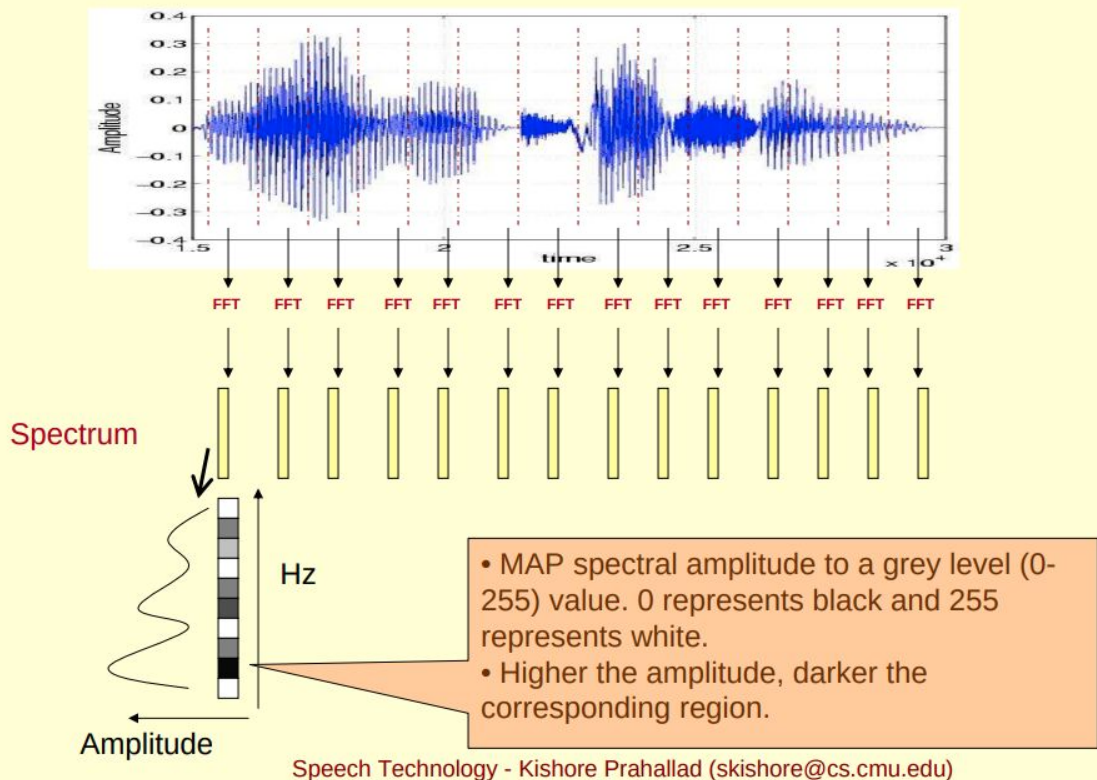


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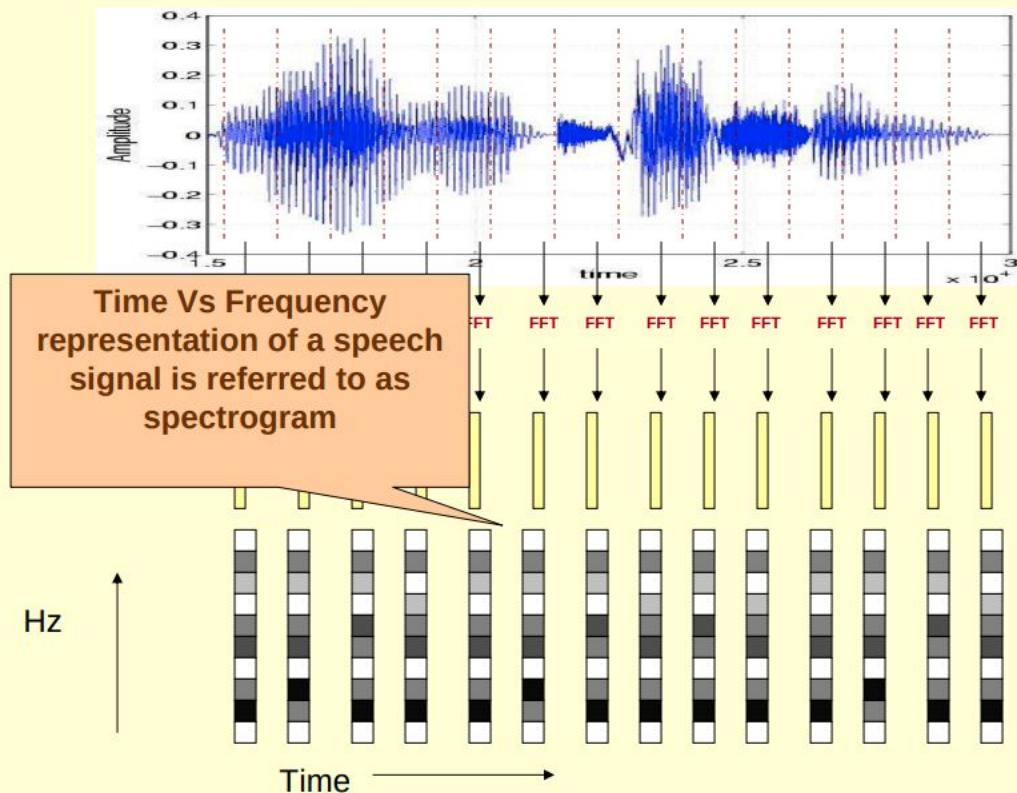
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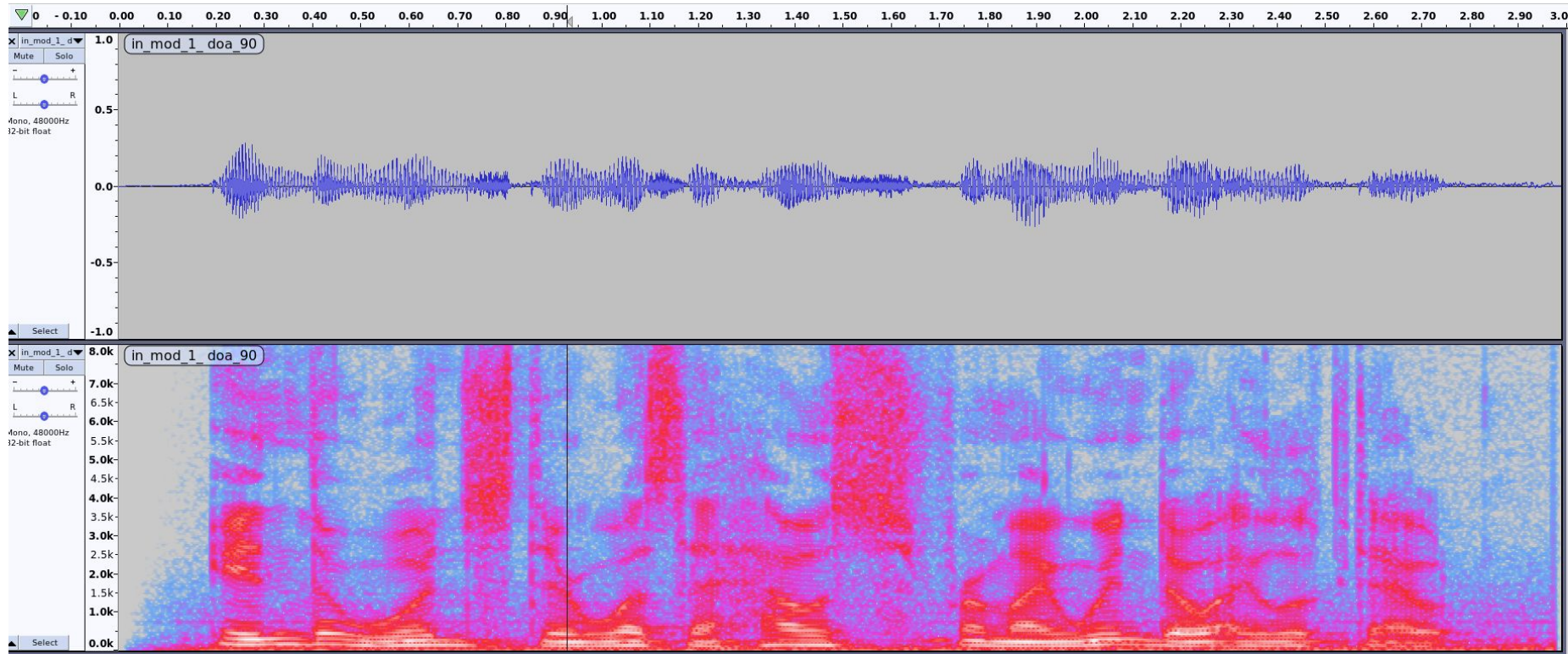
# Classification of Signals

## Temporal / Frequency Resolution Tradeoff



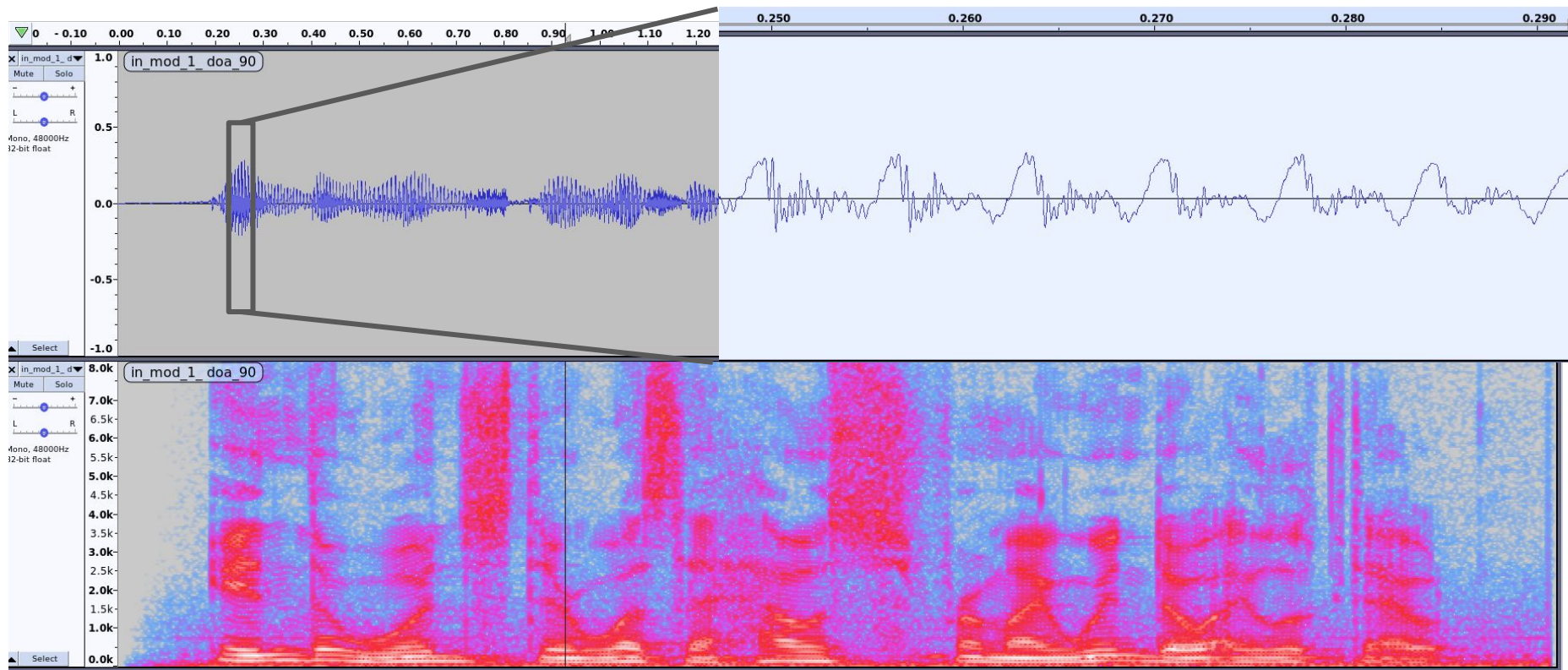


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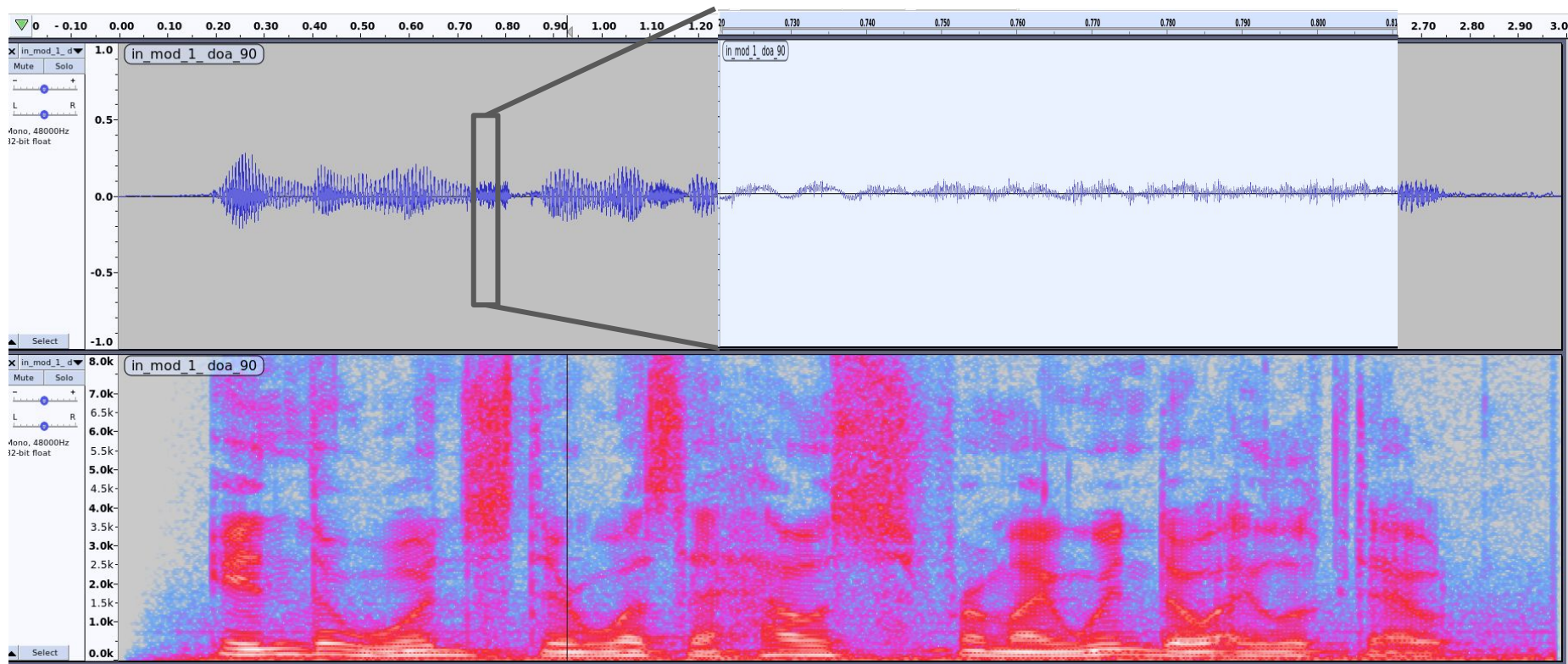




# Classification of Signals



# Classification of Signals



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3. **Energy / RMS calculation**

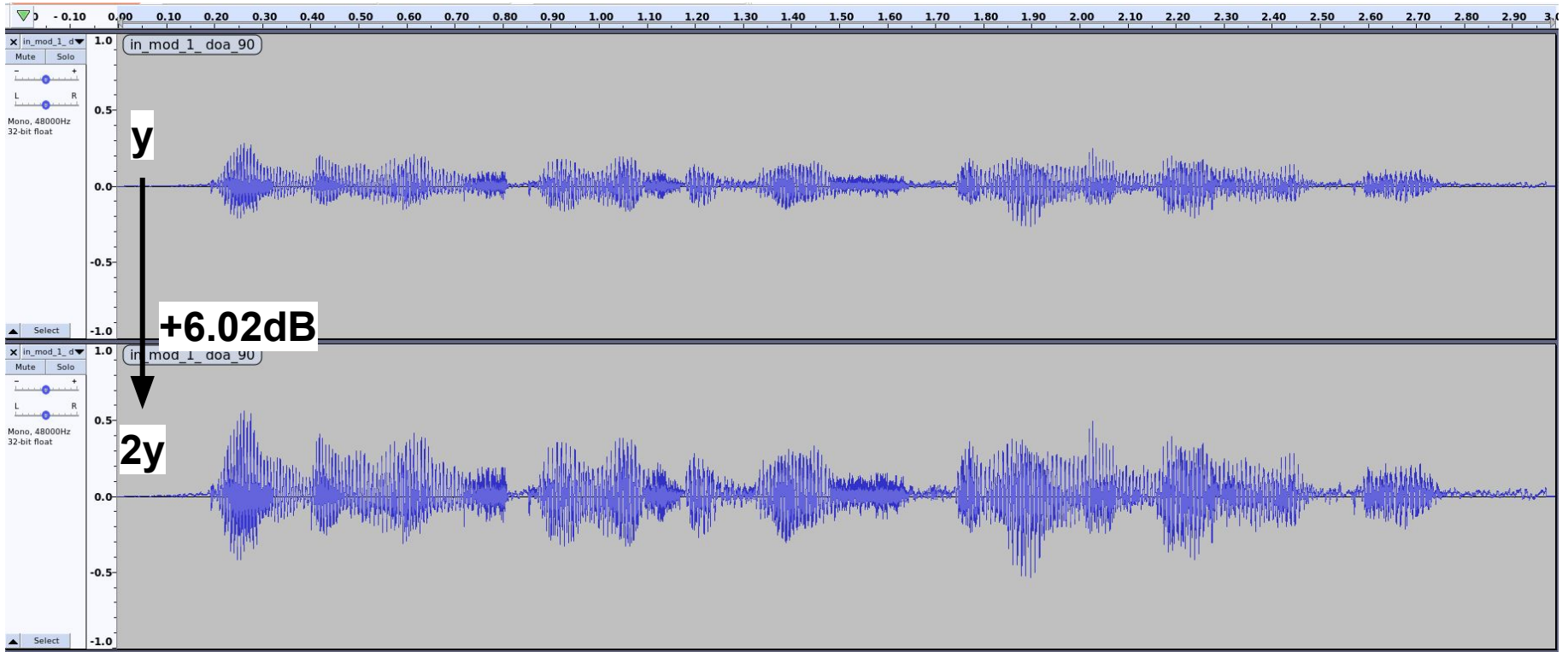
# Energy & RMS

- Sometimes we want to represent some “trends” of signal, but its average has a (zero) constant value.
- 2 accepted measures for an ‘alternative’ average: RMS and Energy
  - RMS: Root-Mean-Squared. Most books define this as the “amount of AC power that produces the same heating effect as an equivalent DC power”
  - Energy: defined as the area under the squared magnitude of the considered signal
- Usually calculated in chunks with hop.

$$E_s = \sum_{n=-\infty}^{\infty} |x(n)|^2 \quad RMS = \sqrt{\frac{1}{n} \sum_i x_i^2}$$

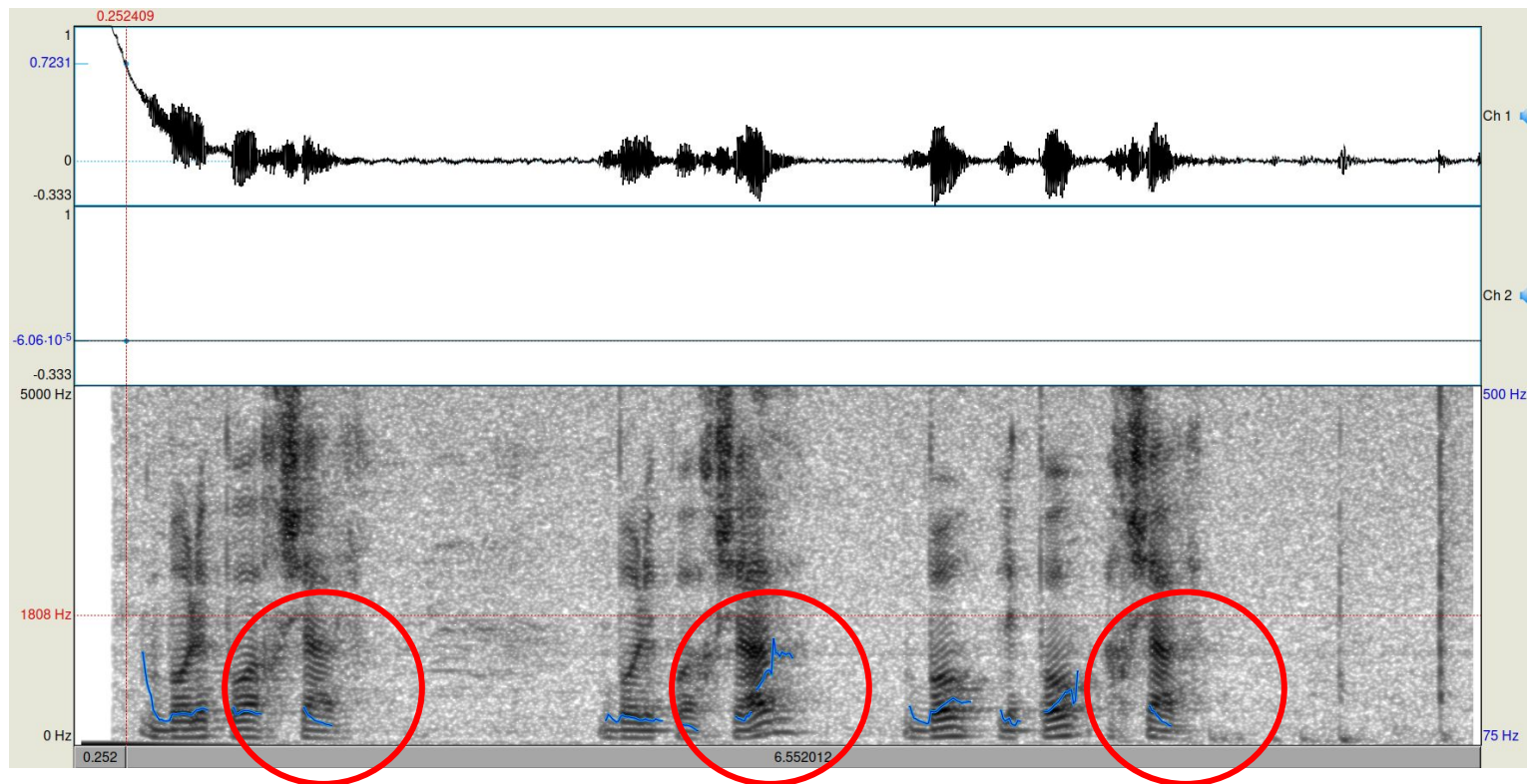


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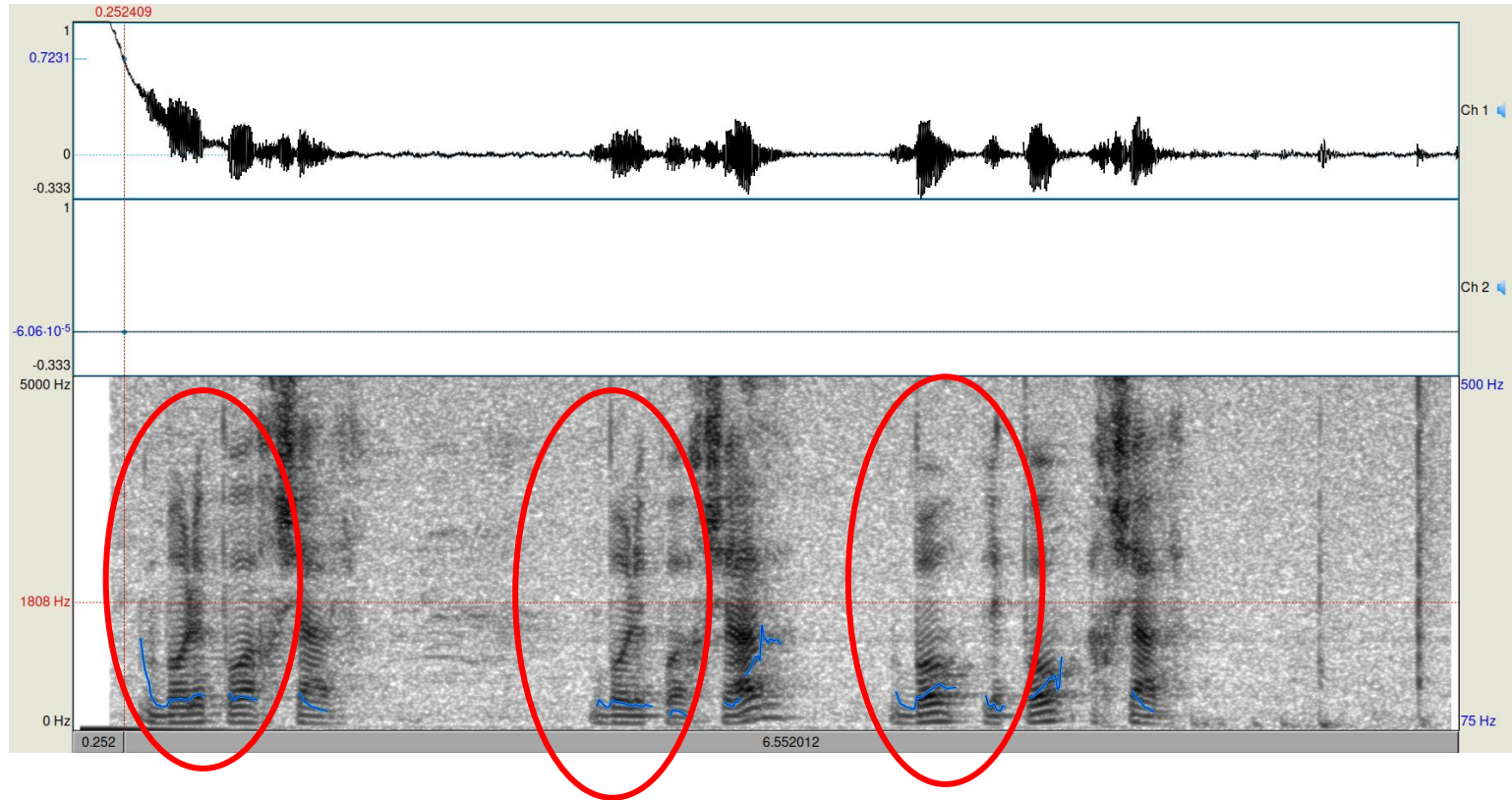




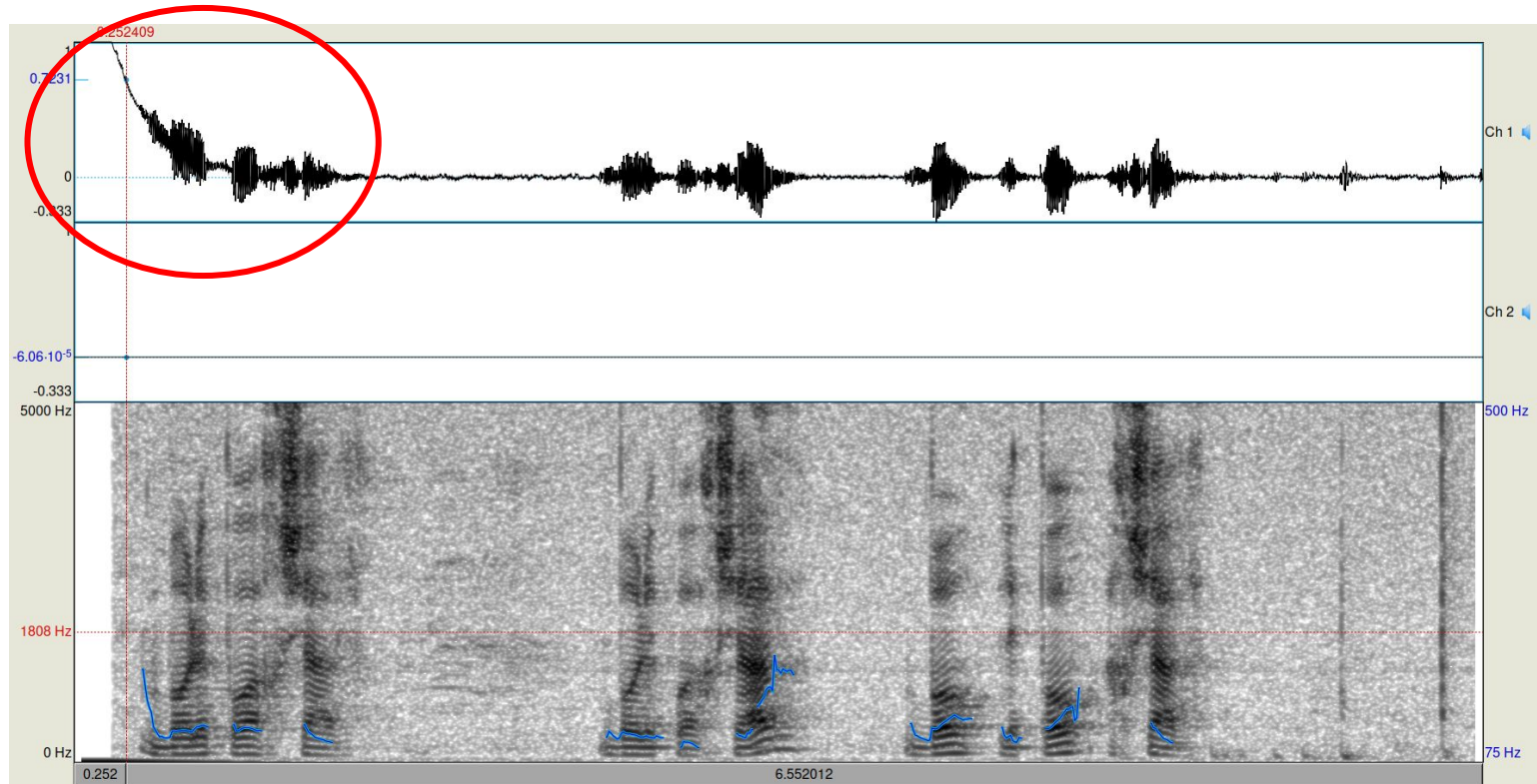
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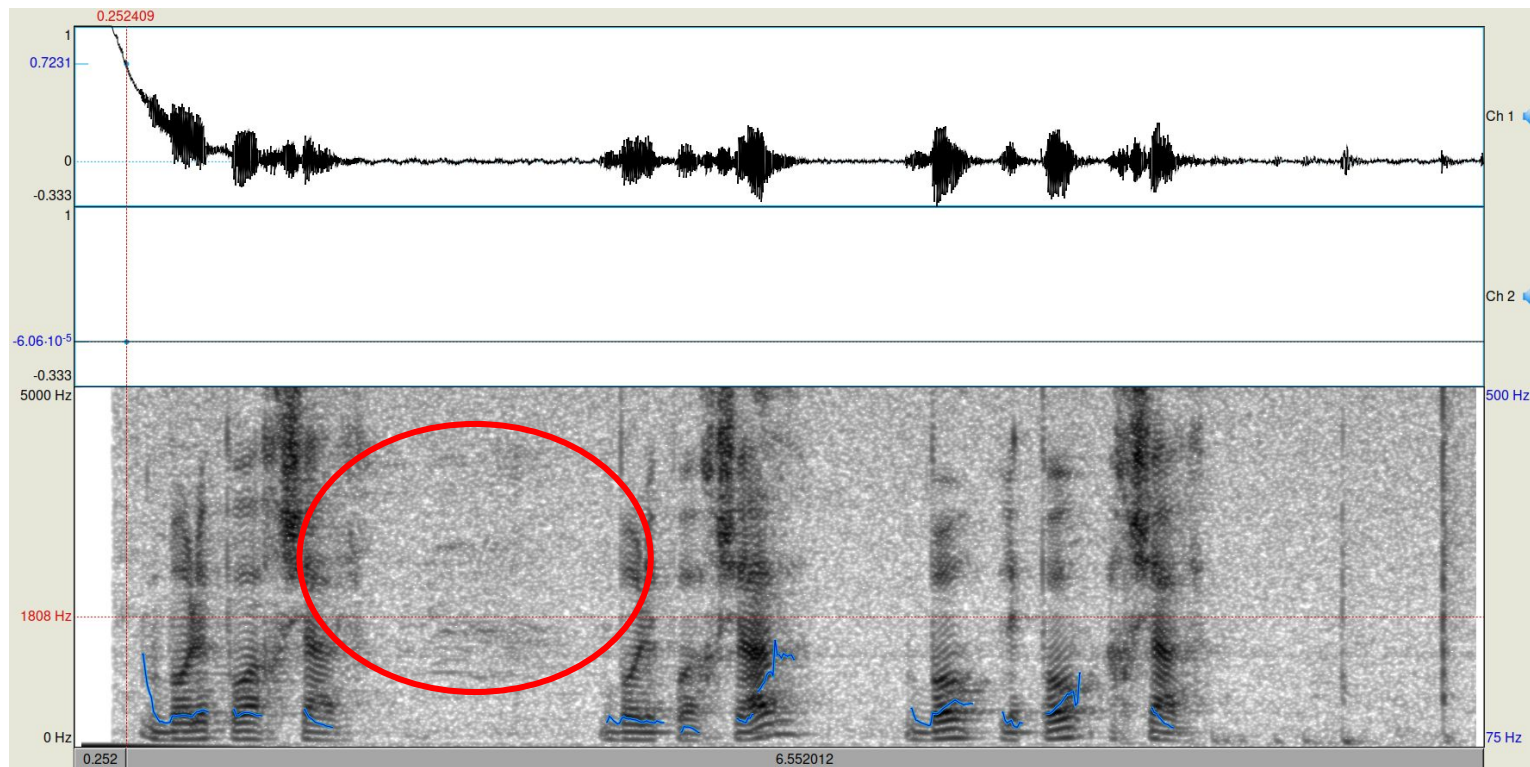


# Energy & RMS





# Energy & RMS



# Code

```
83 def show_spectrogram(fpath: str,  
84                       win_length_sec: float = 0.025,  
85                       hop_length_sec: float = 0.01,  
86                       ):  
87     # Load the audio file  
88     audio, sr = librosa.load(fpath, sr=48000)  
89  
90     # Compute the STFT  
91     win_length_samples = int(win_length_sec * sr)  
92     hop_length_samples = int(hop_length_sec * sr)  
93     n_fft = win_length_samples  
94     stft = librosa.stft(audio,  
95                          n_fft=n_fft,  
96                          win_length=win_length_samples,  
97                          hop_length=hop_length_samples)  
98     stft_db = librosa.amplitude_to_db(abs(stft), ref=np.max)  
99  
100    # Display the STFT  
101    librosa.display.specshow(stft_db, sr=sr, y_axis='linear', x_axis='time')  
102    plt.colorbar(format='%+2.0f dB')  
103    plt.xlabel('Time (s)') # Custom x-axis label  
104    plt.ylabel('Frequency (Hz)') # Custom y-axis label  
105    plt.title('STFT of Audio Signal')  
106    plt.show()
```