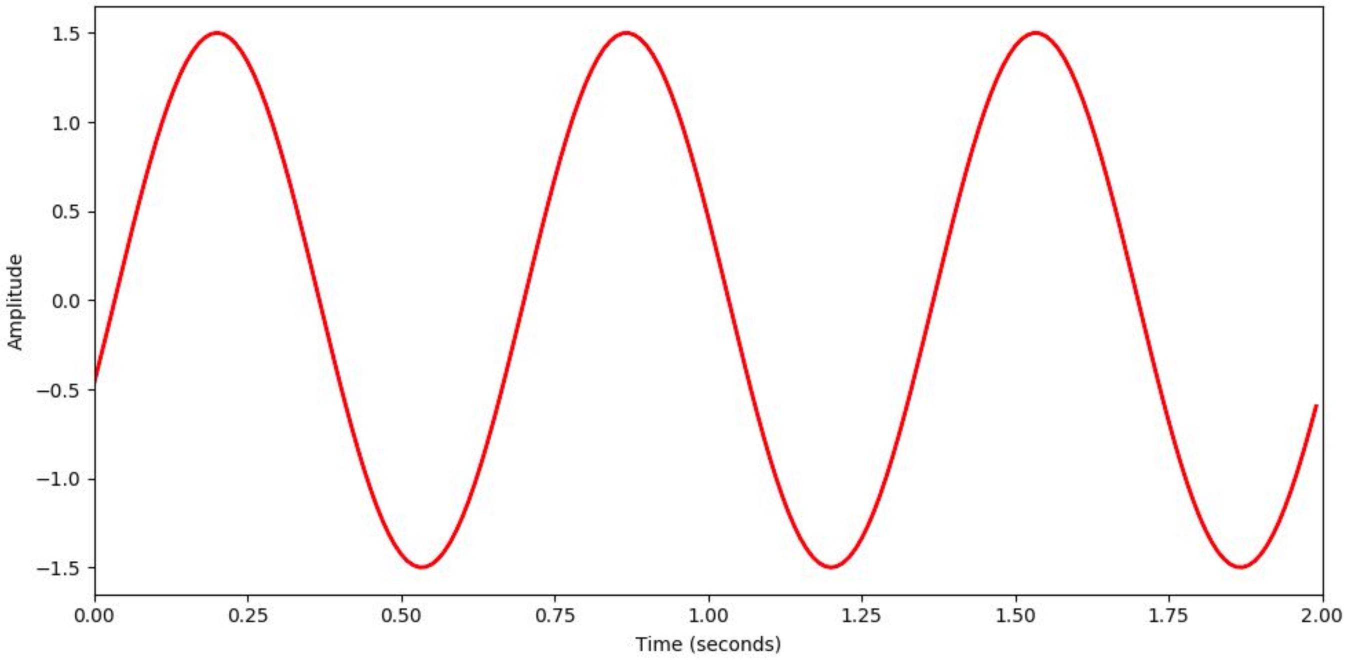
Understanding audio data for deep learning

Valerio Velardo

Sound

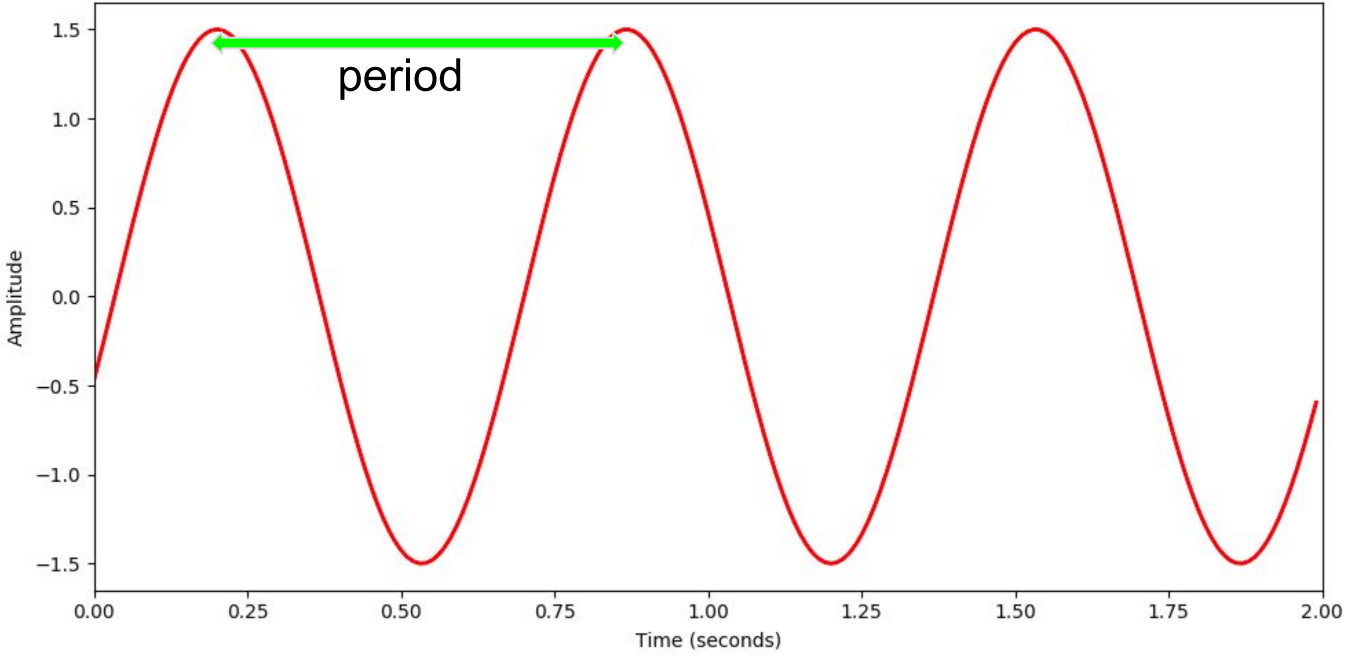
- Produced by the vibration of an object
- Vibrations determine oscillation of air molecules
- Alternation of air pressure causes a wave

Waveform



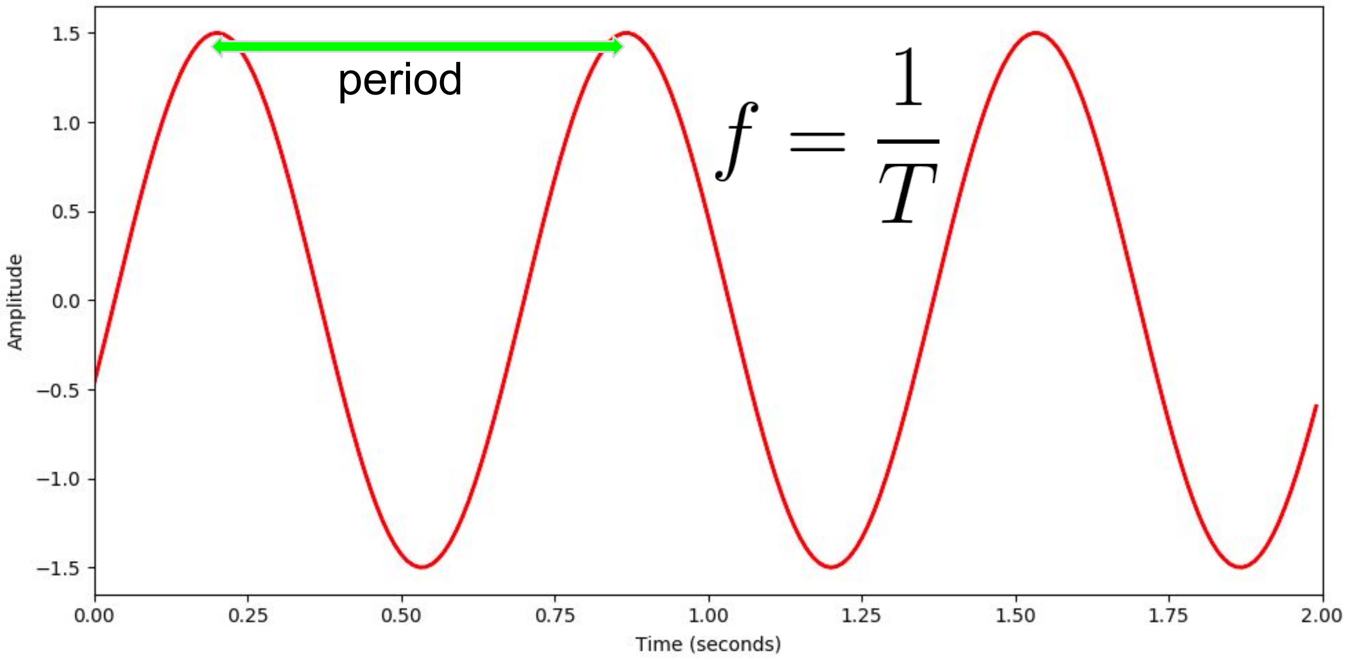
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Amplitude
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Time (seconds)

Waveform

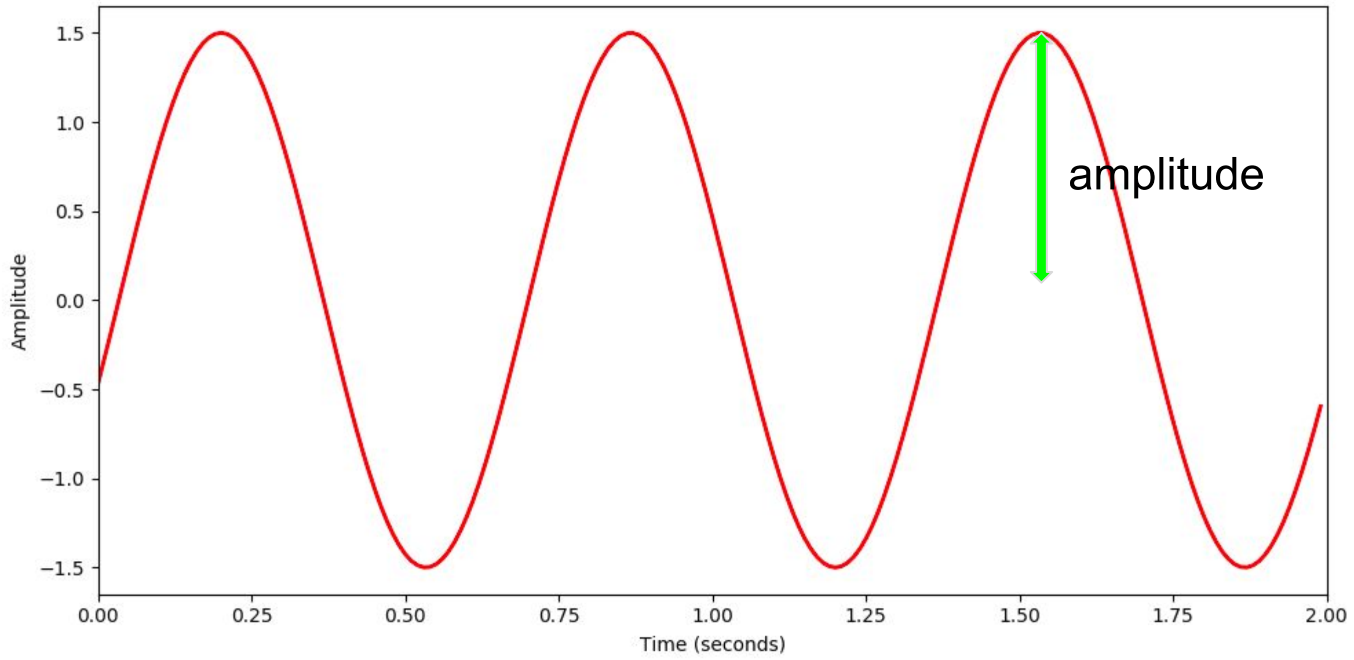


period
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Amplitude
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Time (seconds)

Waveform

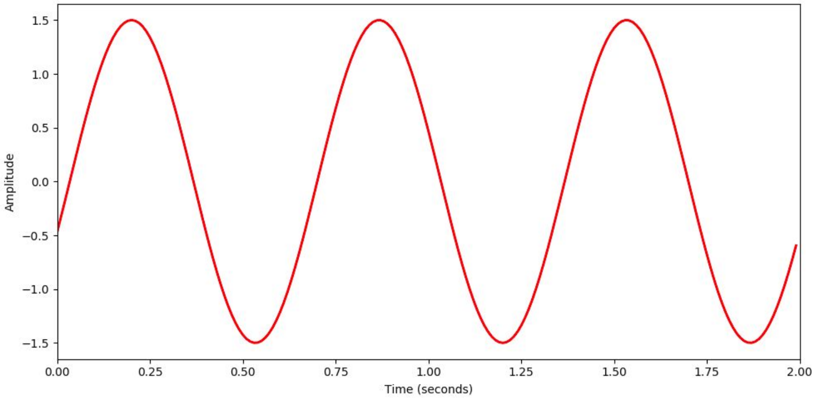

period
$f = \frac{1}{T}$
Amplitude
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Time (seconds)

Waveform



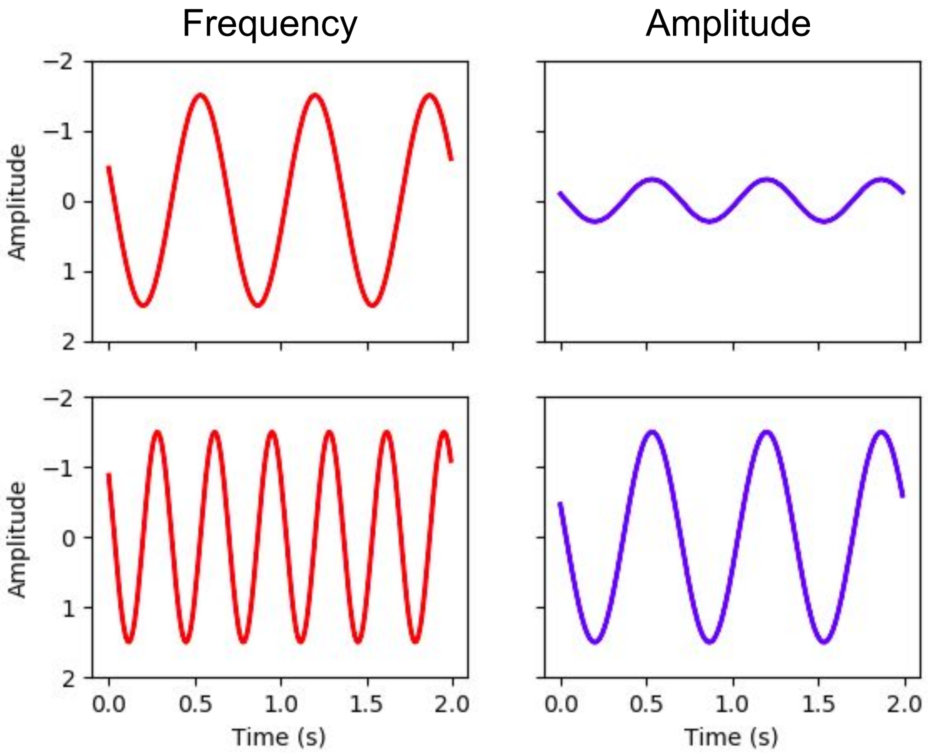
amplitude
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Amplitude
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Time (seconds)

Waveform

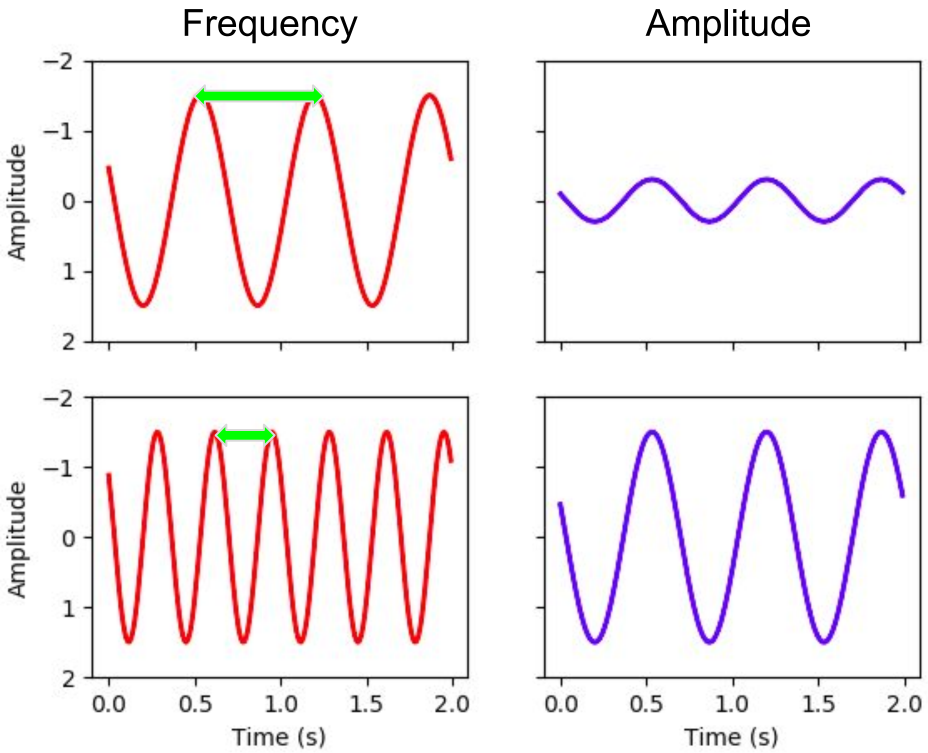


$$y(t) = A\sin(2\pi f t + \varphi)$$

Frequency/pitch and amplitude/loudness

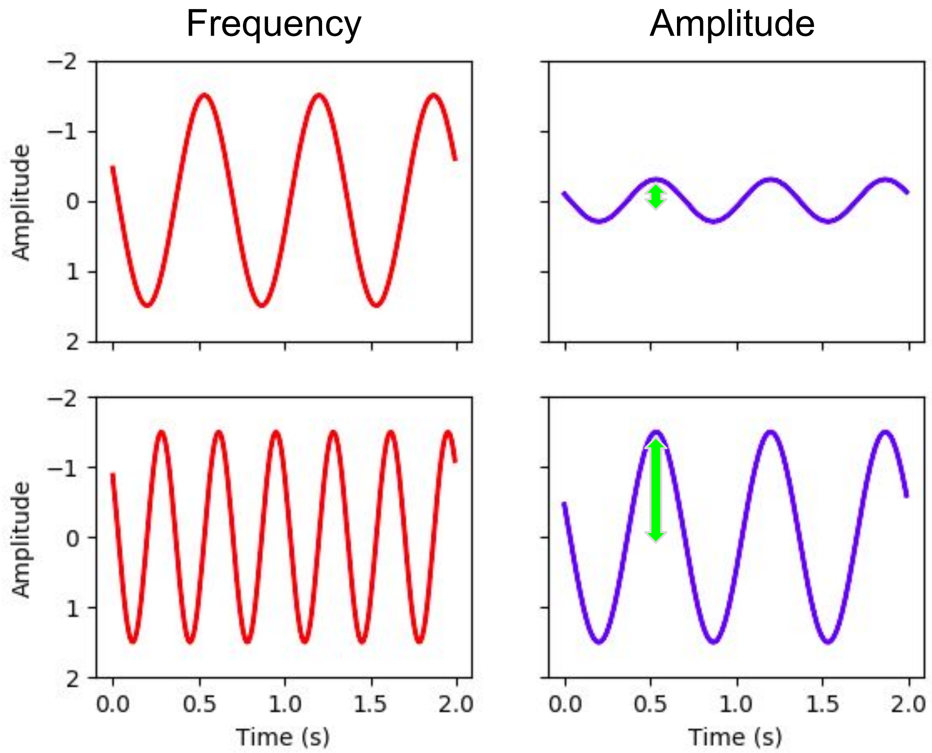


Frequency/pitch and amplitude/loudness



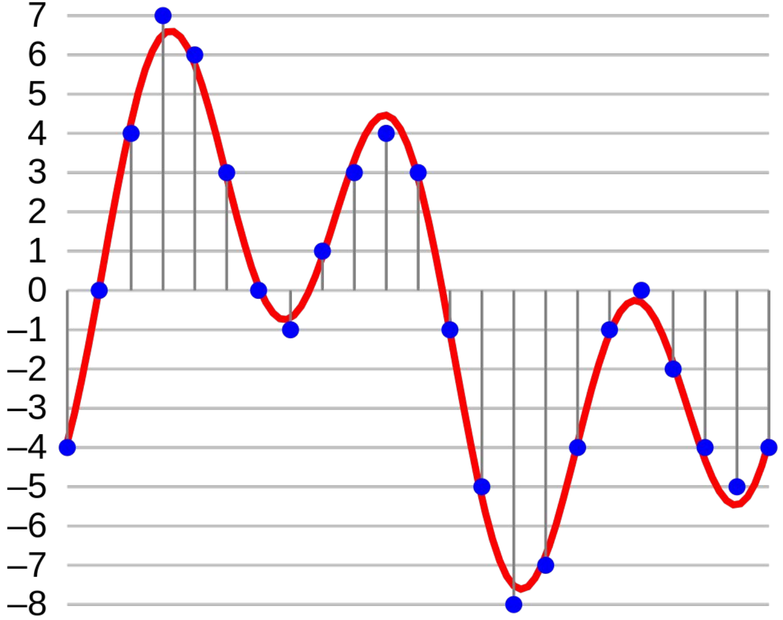
higher frequency -> higher pitch

Frequency/pitch and amplitude/loudness



larger amplitude -> louder

Analog digital conversion (ADC)



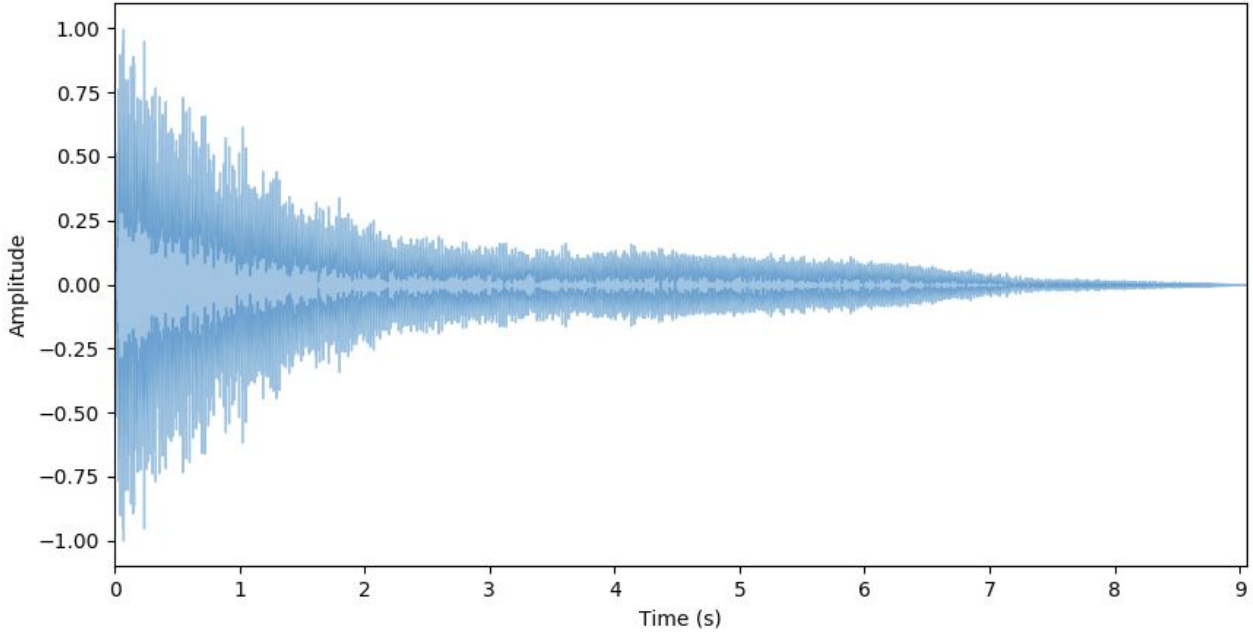
- Signal sampled at uniform time intervals
- Amplitude quantised with limited number of bits

Analog digital conversion (ADC)

Sample rate = 44,100 Hz

Bit depth = 16 bits/channel

A real-world sound wave (piano key)



Fourier transform

- Decompose complex periodic sound into sum of sine waves oscillating at different frequencies

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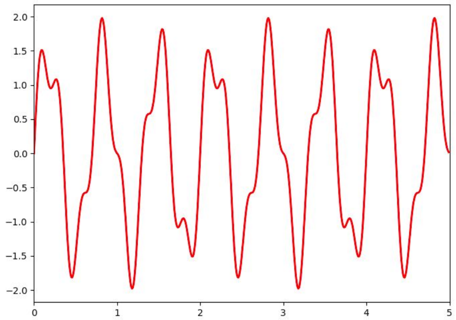
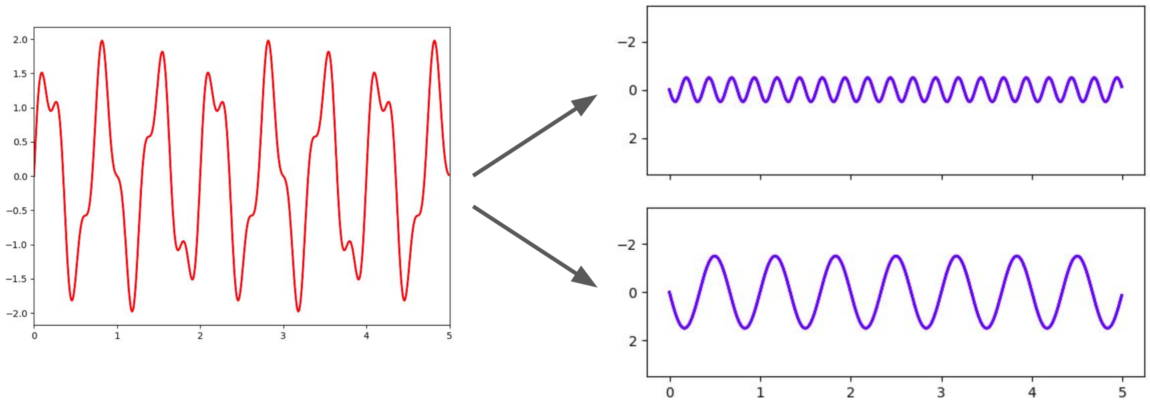


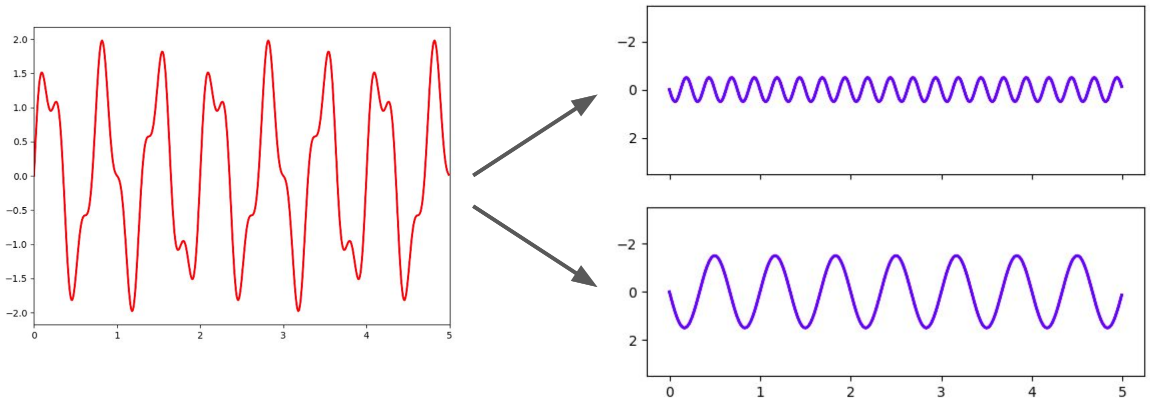
Fourier transform

- Decompose complex periodic sound into sum of sine waves oscillating at different frequencies



Fourier transform

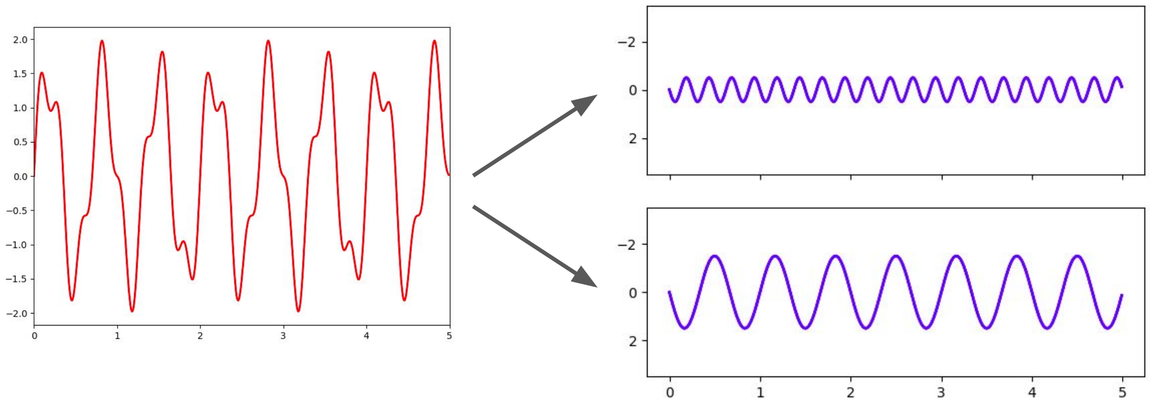
- Decompose complex periodic sound into sum of sine waves oscillating at different frequencies



$$\boxed{s = A_1 \sin(2\pi f_1 t + \varphi_1) + A_2 \sin(2\pi f_2 t + \varphi_2)}$$

Fourier transform

- Decompose complex periodic sound into sum of sine waves oscillating at different frequencies



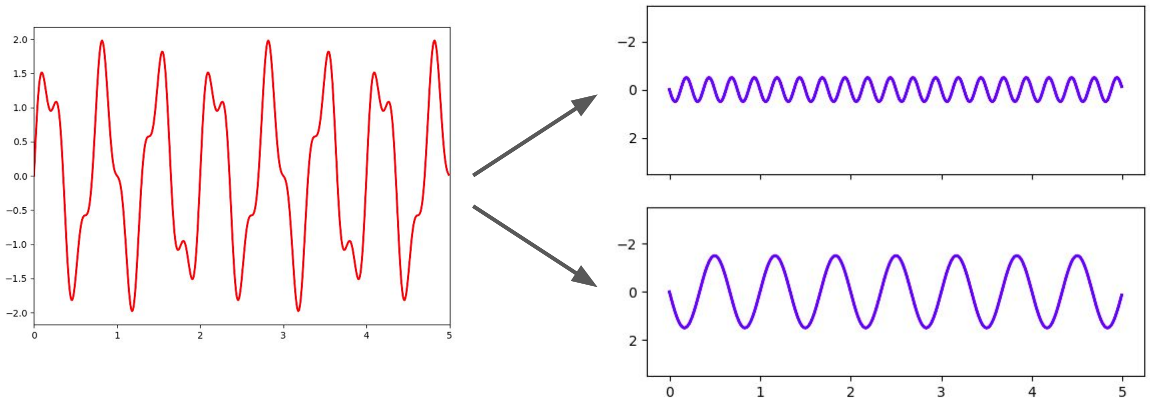
$$\boxed{A_1 = 0.5, f_1 = 4, \varphi_1 = 0}$$

$$\boxed{A_2 = 1.5, f_2 = 1.5, \varphi_2 = 0}$$

$$s = A_1 \sin(2\pi f_1 t + \varphi_1) + A_2 \sin(2\pi f_2 t + \varphi_2)$$

Fourier transform

- Decompose complex periodic sound into sum of sine waves oscillating at different frequencies



$\boxed{A_1 = 0.5}, f_1 = 4, \varphi_1 = 0$

$\boxed{A_2 = 1.5}, f_2 = 1.5, \varphi_2 = 0$

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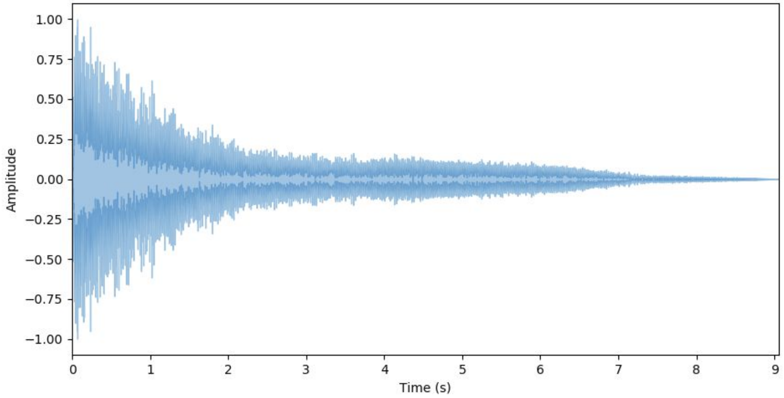
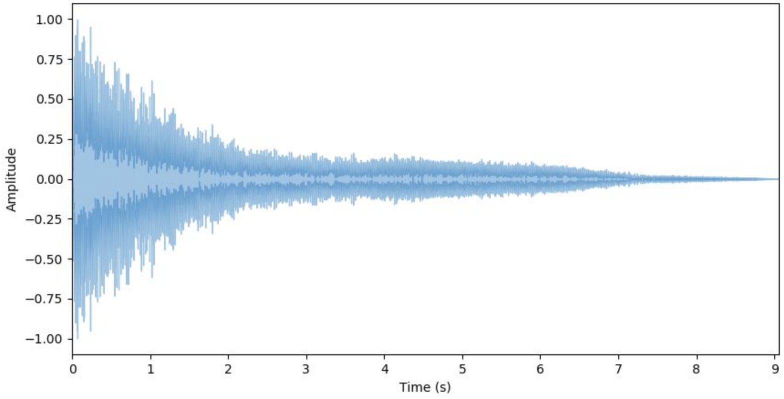
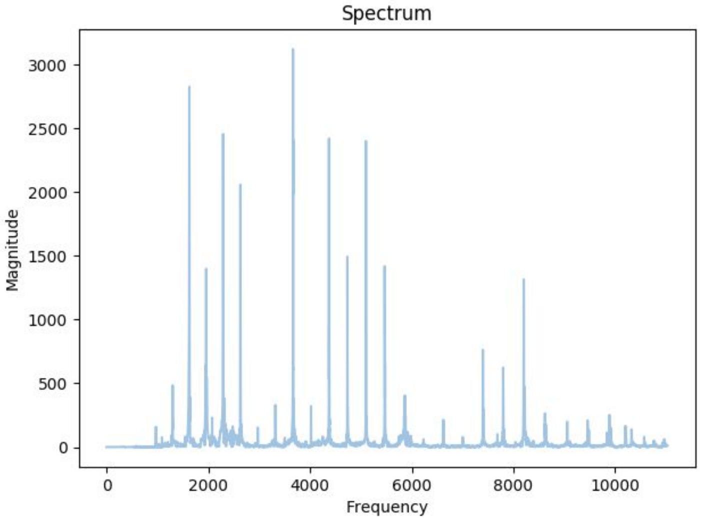
Fourier transform



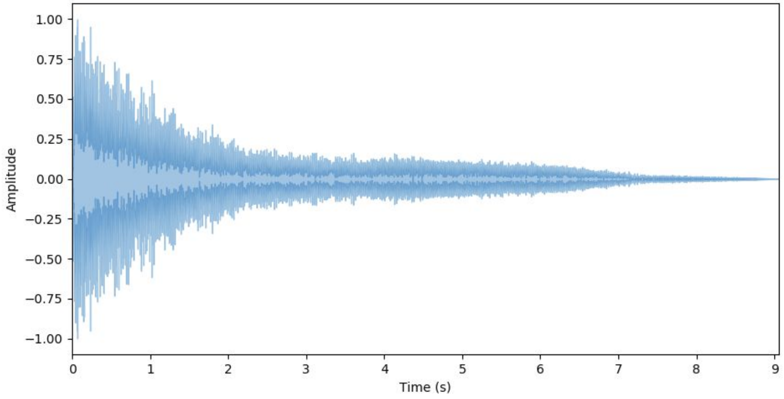
Fourier transform



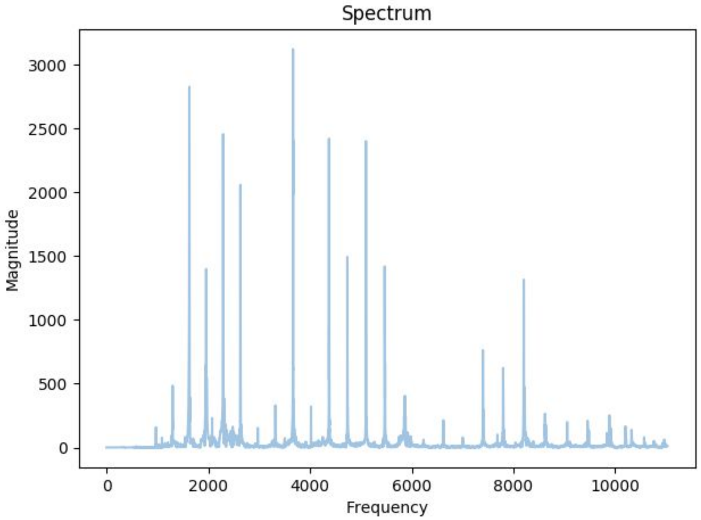
FFT



Fourier transform



FFT

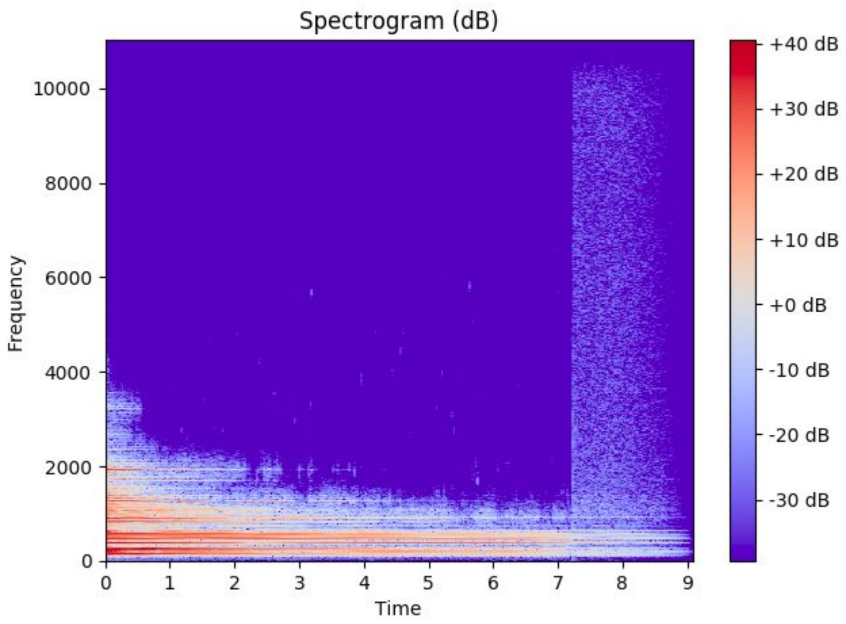


- From *time domain* to *frequency domain*
- No time information

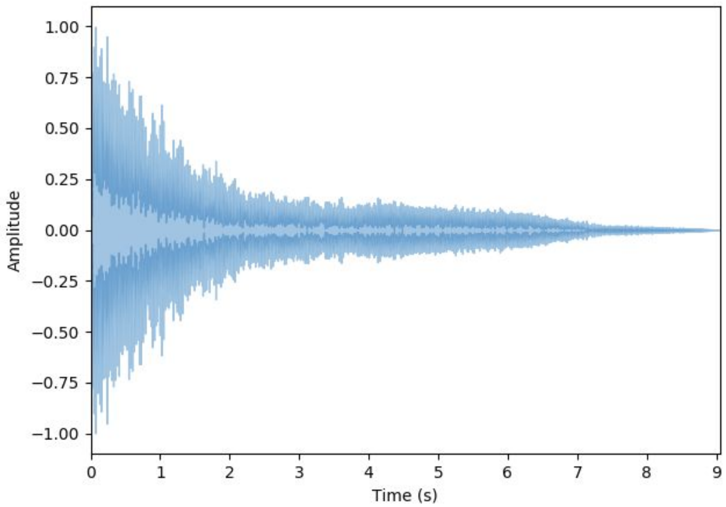
Short Time Fourier Transform (STFT)

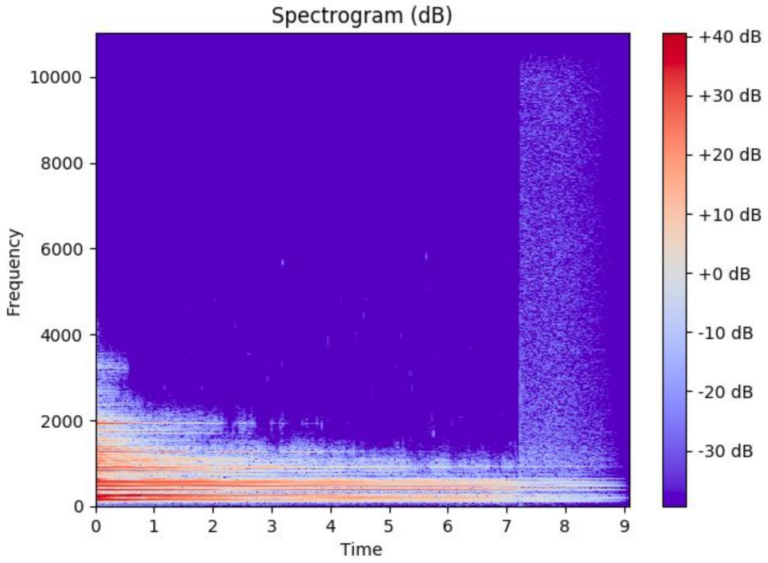
- Computes several FFT at different intervals
- Preserves time information
- Fixed frame size (e.g., 2048 samples)
- Gives a *spectrogram* (time + frequency + magnitude)

Short Time Fourier Transform (STFT)



Short Time Fourier Transform (STFT)





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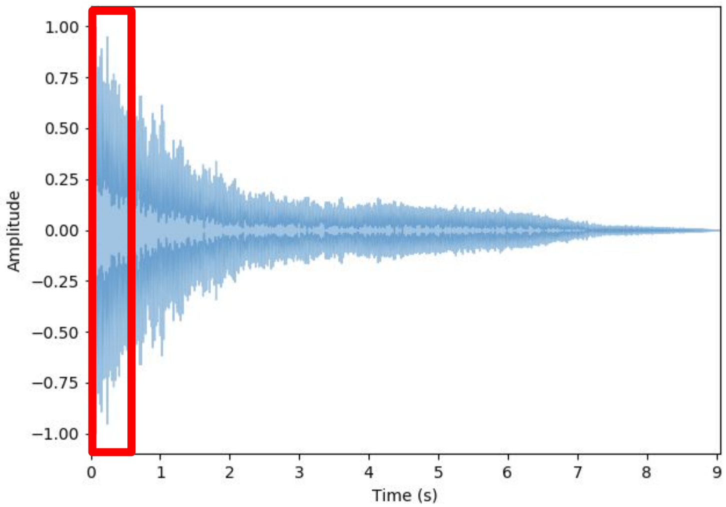

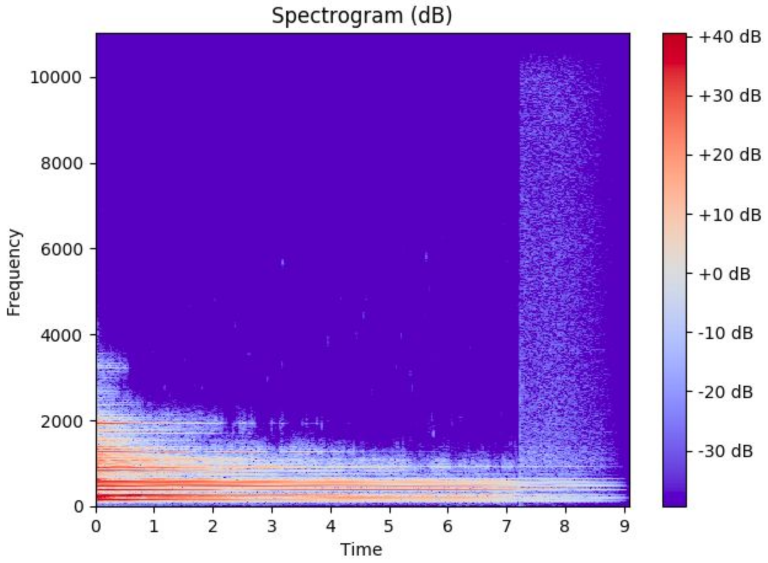

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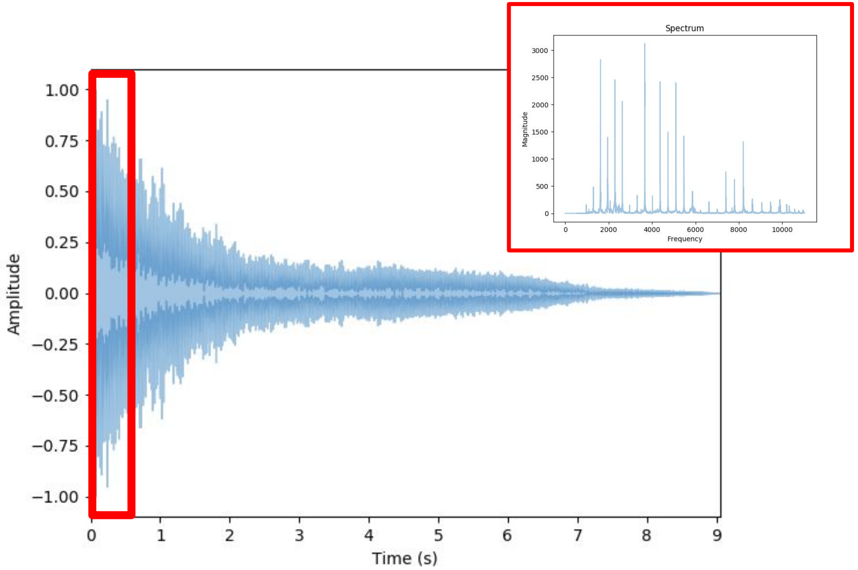

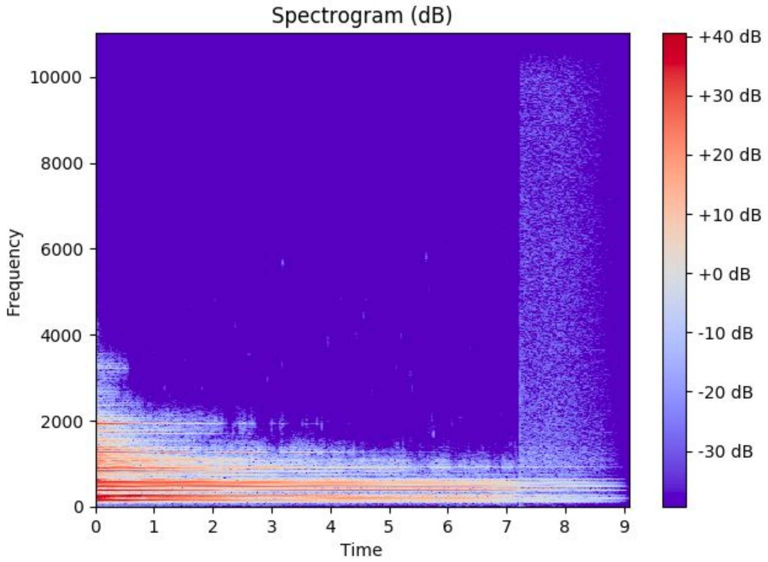

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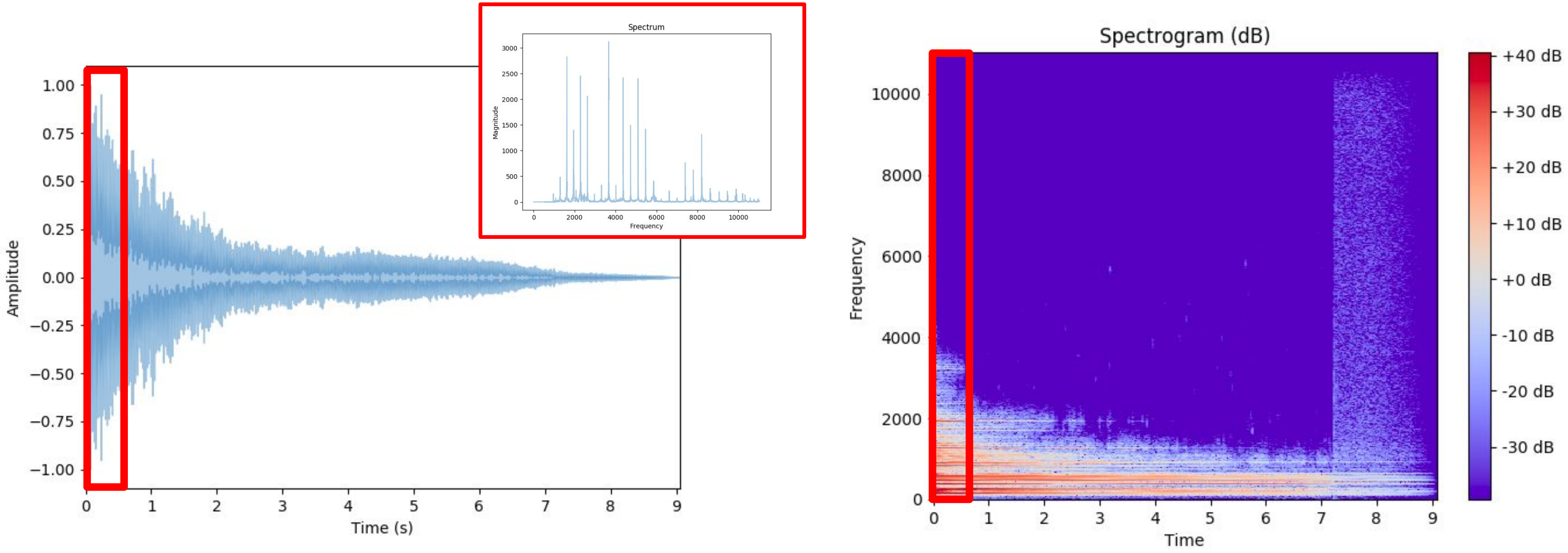

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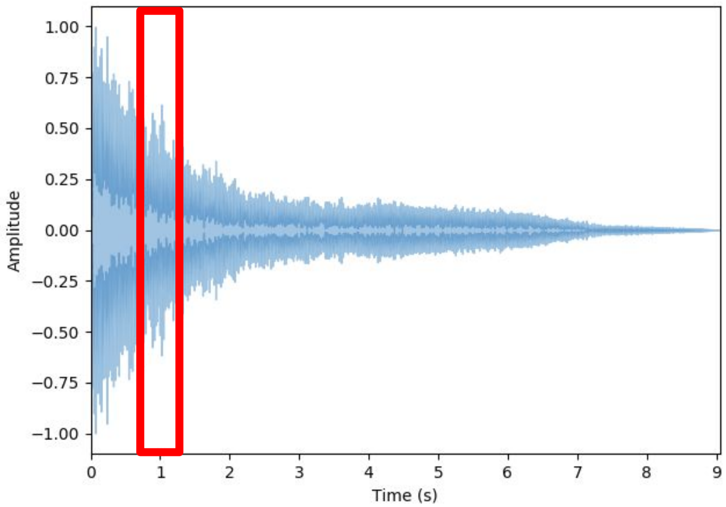

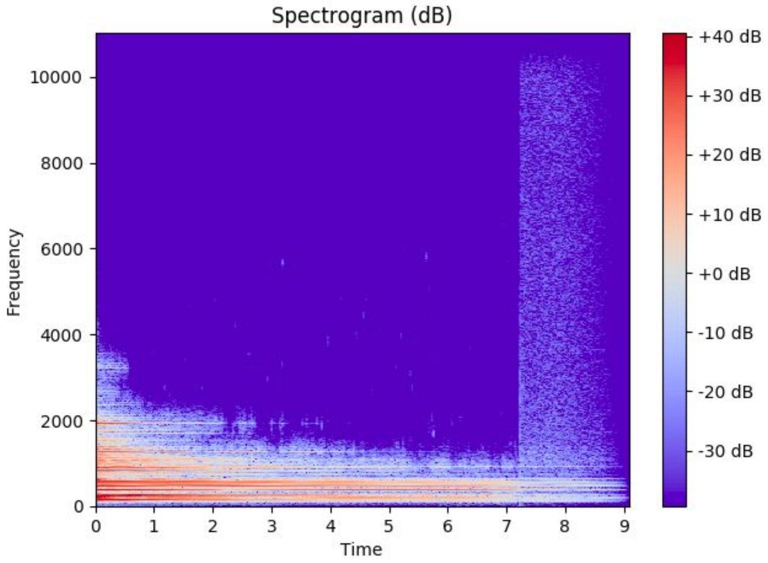

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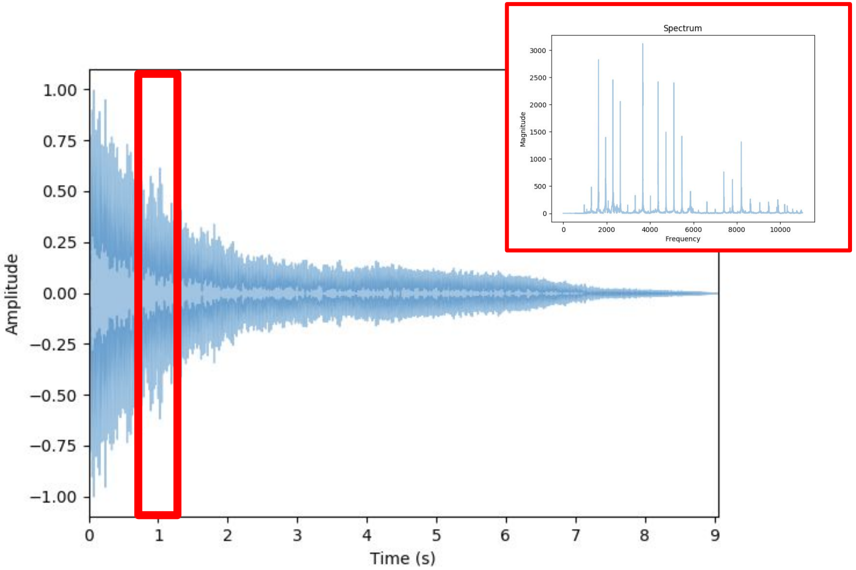

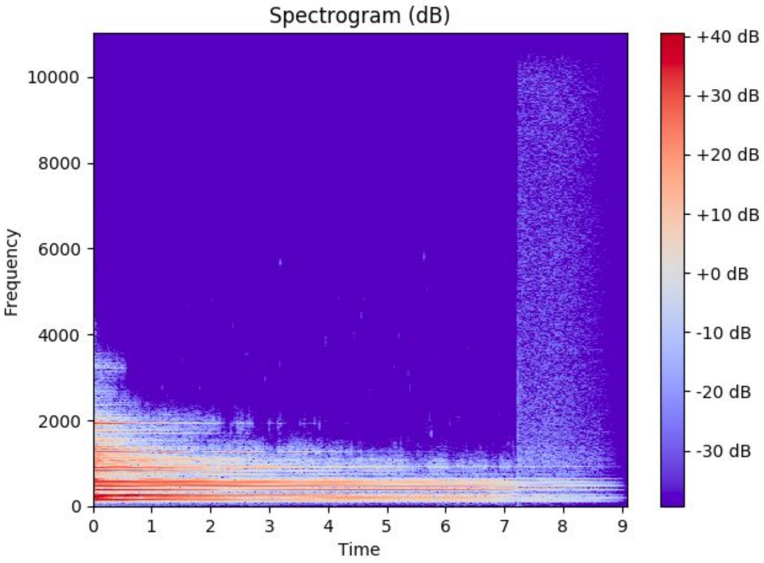

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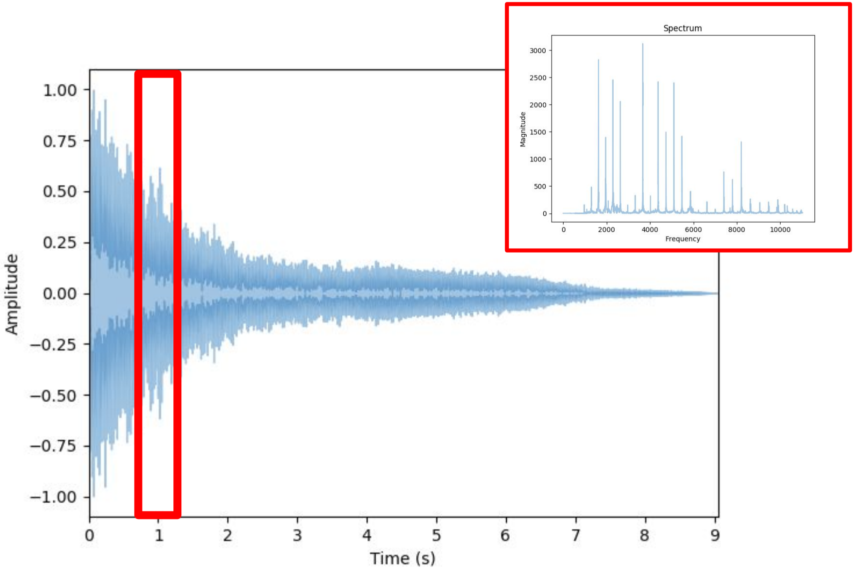

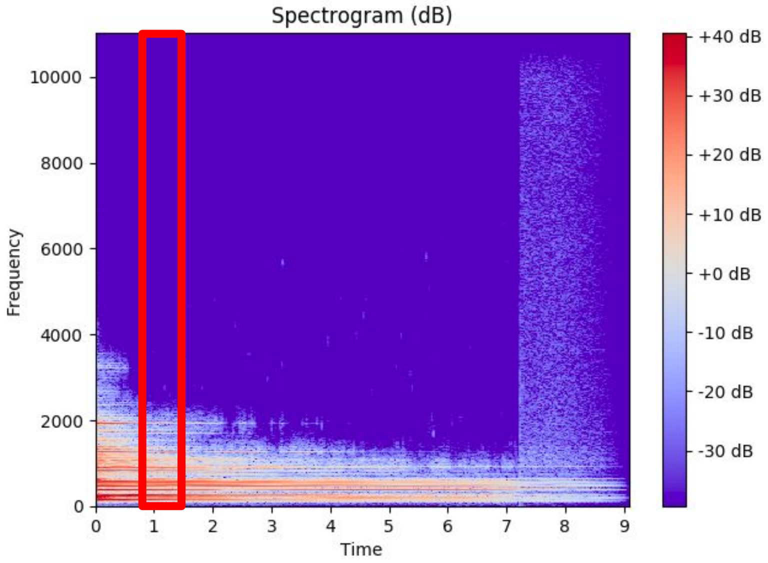

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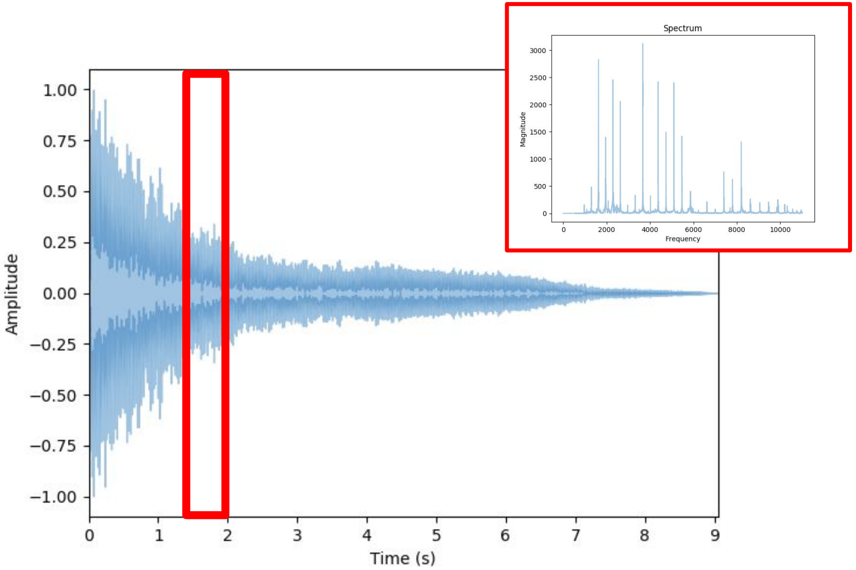
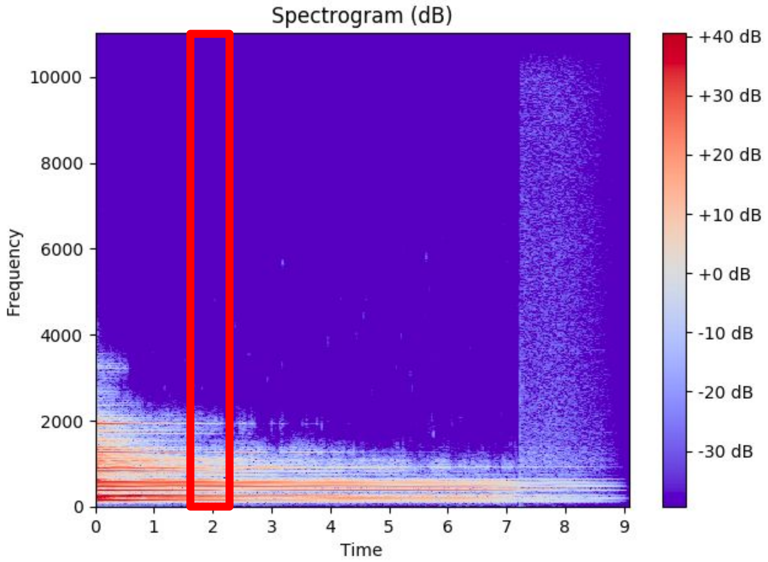
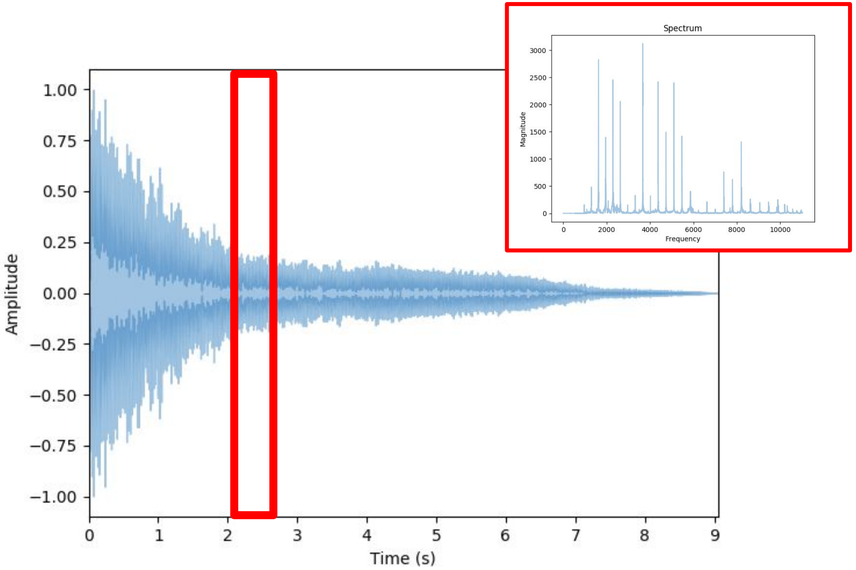
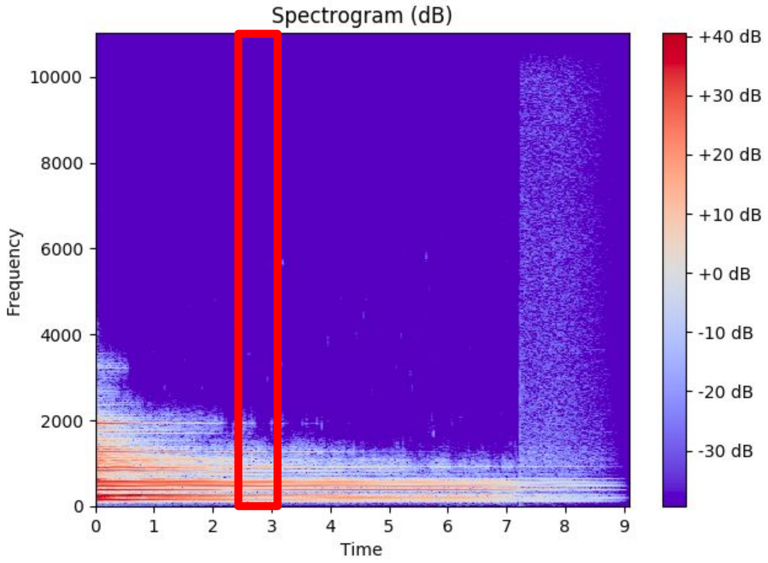


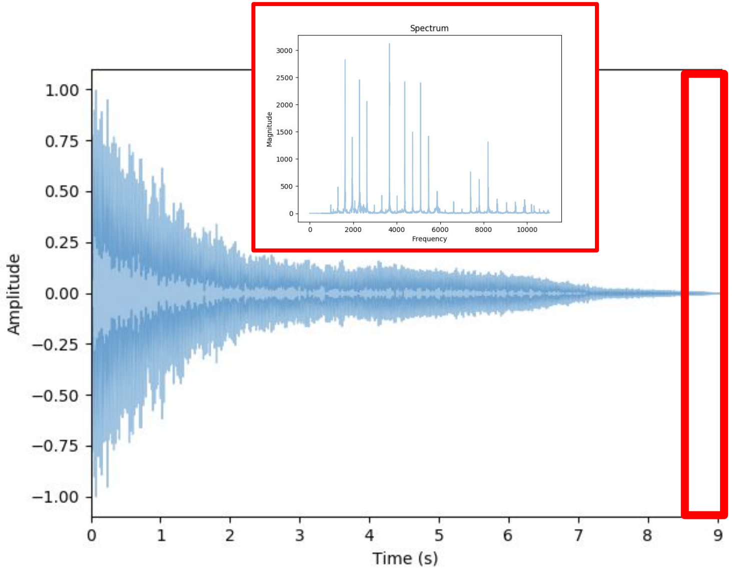


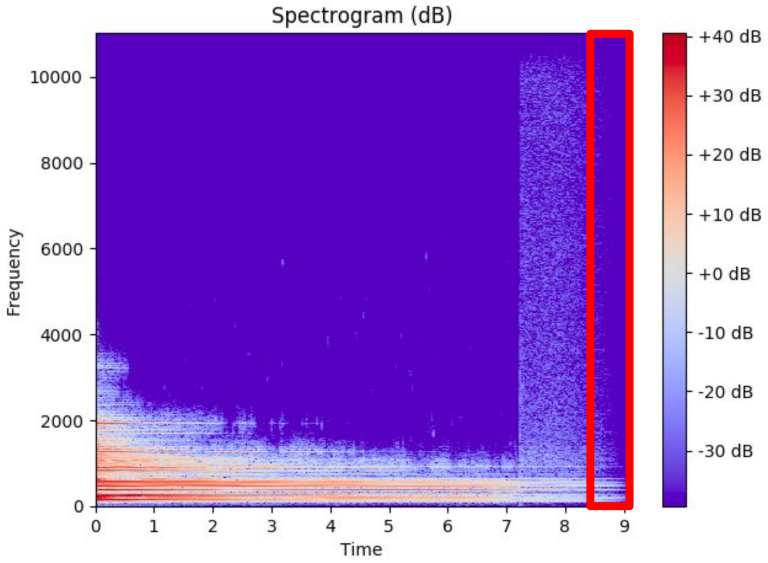
Short Time Fourier Transform (STFT)



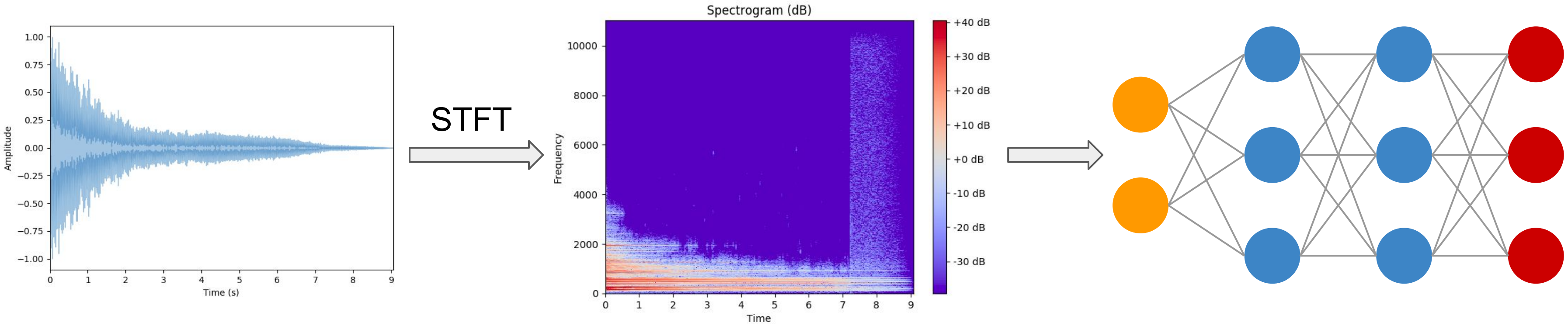


Short Time Fourier Transform (STFT)

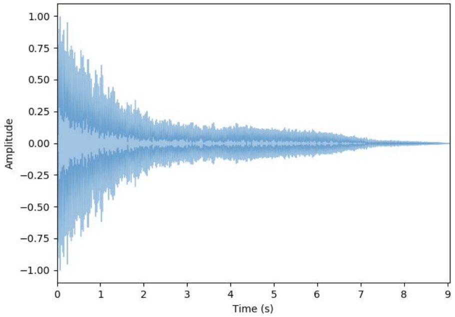




DL pre-proprocessing pipeline for audio data



Traditional ML pre-proprocessing pipeline for audio data



- Amplitude envelope
- Spectral centroid
- 0-crossing rate
- Spectral flux
- ...

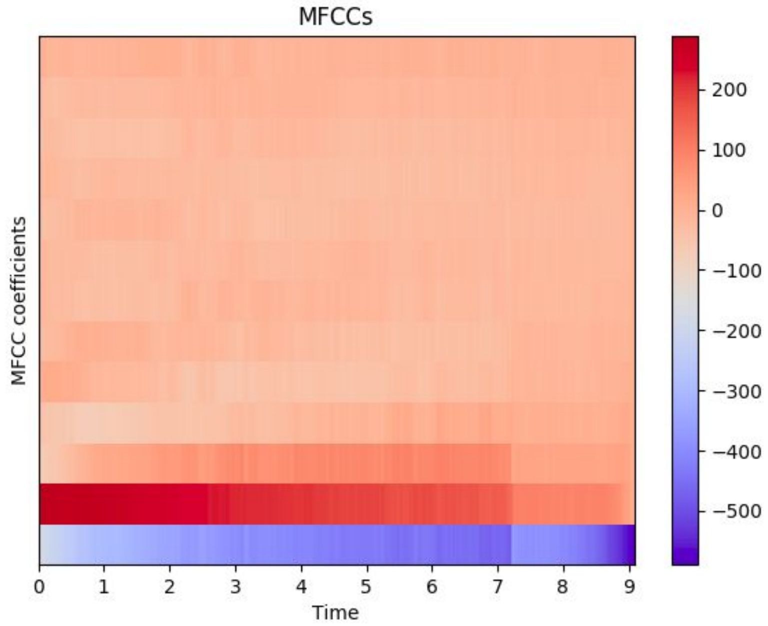
ML algorithm

- Feature engineering
- Perform STFT
- Extract time + frequency domain features

Mel Frequency Cepstral Coefficients (MFCCs)

- Capture timbral/textural aspects of sound
- Frequency domain feature
- Approximate human auditory system
- 13 to 40 coefficients
- Calculated at each frame

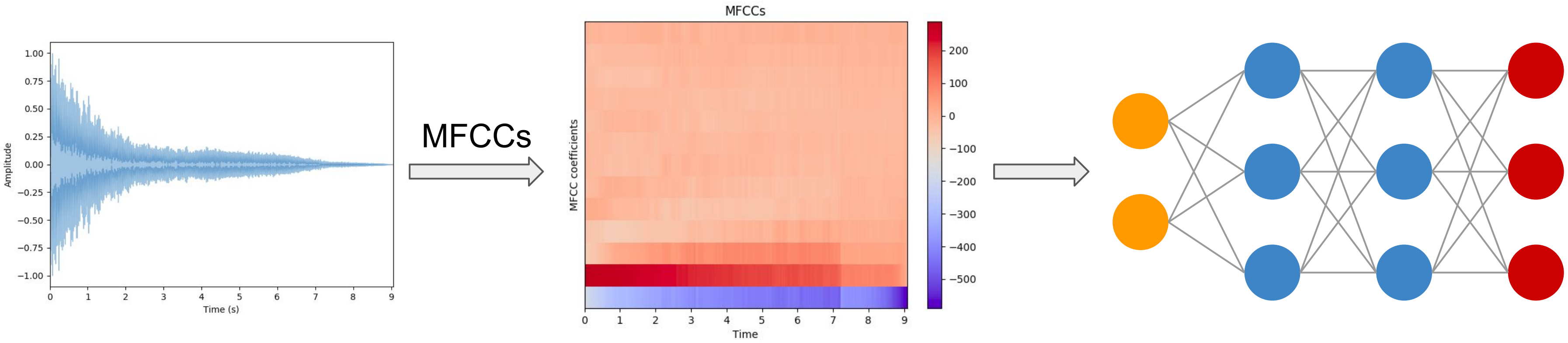
Mel Frequency Cepstral Coefficients (MFCCs)



MFCCs applications

- Speech recognition
- Music genre classification
- Music instrument classification
- ...

DL pre-proprocessing pipeline for audio data



What’s up next?

- Perform FFT and STFT with Python
- Extract MFCCs
- Get familiar with *librosa*