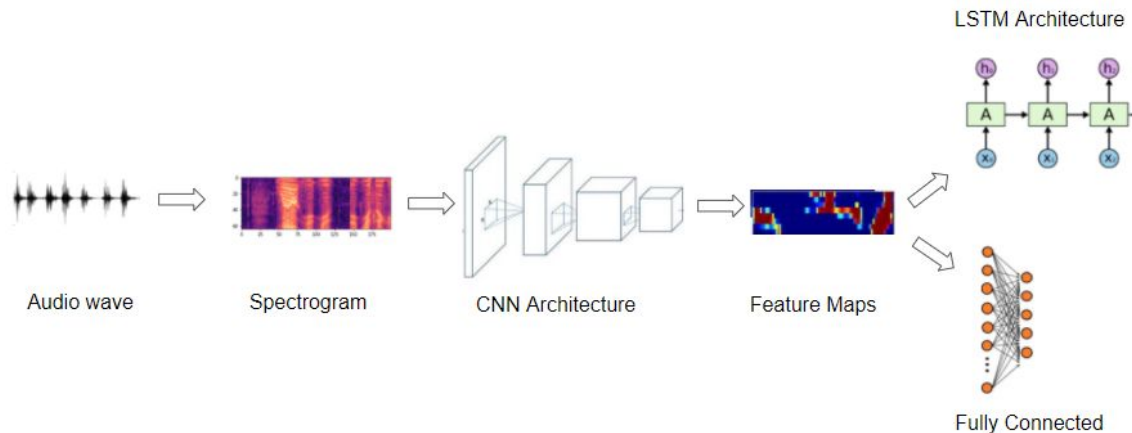


Exploring the best way to represent an audio signal for ML model

On the example of audio classification

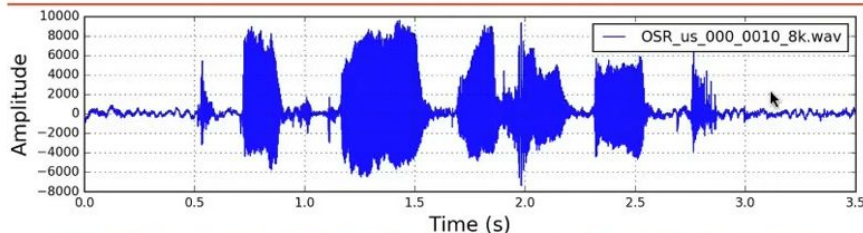
- ★ Raw signal data
- ★ Short-Time Fourier-Transform (STFT)
- ★ Mel-spaced Filterbank
- ★ Mel Spectrogram
- ★ Discrete Cosine Transform (DCT)



Looking closely at audio signal post-processing



Mel-Spectrogram and Mel-Frequency Cepstral Coefficients (MFCCs)

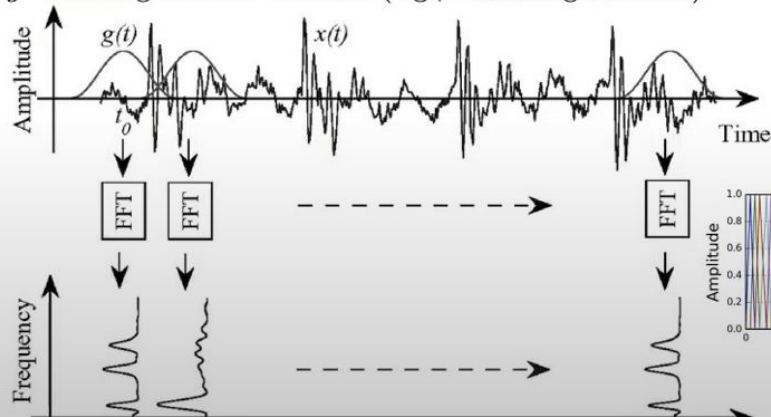


<https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html>

Short-Time Fourier-Transform (STFT)

$x \rightarrow$ signal in the time domain (e.g., $x \in \mathbb{R}^{28,200=3.525 \text{ seconds} \times 8,000 \text{ Hz}}$)
sampling frequency (number of samples per seconds)

$g \rightarrow$ sliding window function (e.g., Hamming function)



$X_i \in \mathbb{R}^{200} \rightarrow i$ -th frame of signal x (25ms frames)

$80 \rightarrow$ frame step (10ms) $\Rightarrow X \in \mathbb{R}^{200 \times 350}$ ($350 = (28,200 - 200)/80$)

$\tilde{X}_i \in \mathbb{C}^K \rightarrow$ discrete Fourier transform of $X_i \Rightarrow \tilde{X} \in \mathbb{C}^{K \times 350}$

$$\tilde{X}_i(k) = \sum_{n=1}^N X_i(n)g(n)e^{-j2\pi kn/N}, k = 1, \dots, K \quad N = 200$$

$K = 257 \rightarrow$ number of discrete Fourier transform coefficients

$P_i(k) = \frac{1}{N} |\tilde{X}_i(k)|^2 \rightarrow$ Periodogram estimate of the power spectrum
 $\Rightarrow P \in \mathbb{R}^{257 \times 350}$

Mel-spaced Filterbank

300 Hz \rightarrow lower frequency

4,000 Hz \rightarrow upper frequency

$M(f) = 1,125 \ln(1 + f/700) \rightarrow$ convert frequency to Mel scale

$M^{-1}(m) = 700(\exp(m/1,125) - 1) \rightarrow$ convert Mel scale to Hz

$M^{-1}(\text{linspace}(M(300), M(4,000), 26 + 2))$ $26 \rightarrow$ number of triangular filters

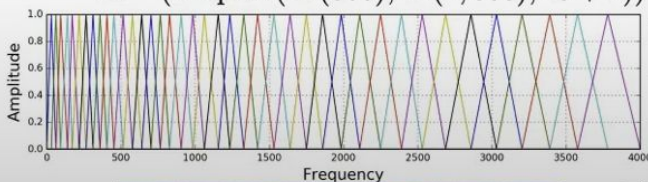
$$T \in \mathbb{R}^{26 \times 257} \Rightarrow E = TP \in \mathbb{R}^{26 \times 350}$$

$E_i(l) \rightarrow$ amount of energy in filter bank l at frame i

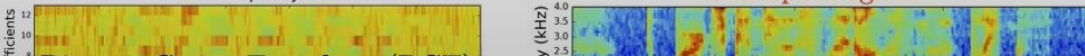
$\log(E) \in \mathbb{R}^{26 \times 350} \rightarrow$ log filter bank energy

<http://practicalcryptography.com/miscellaneous/machine-learning/guide-mel-frequency-cepstral-coefficients-mfccs/>

<https://www.youtube.com/watch?v=WJl-17MNpdE>



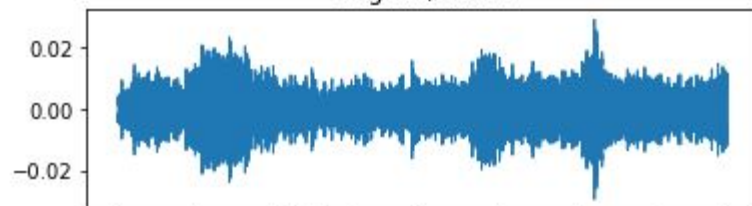
Mel Spectrogram



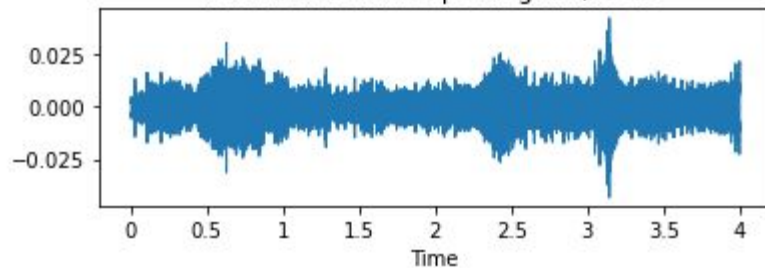
Mel-Spectrogram analysis

original memory use = 176400, melspectrogram = 22080

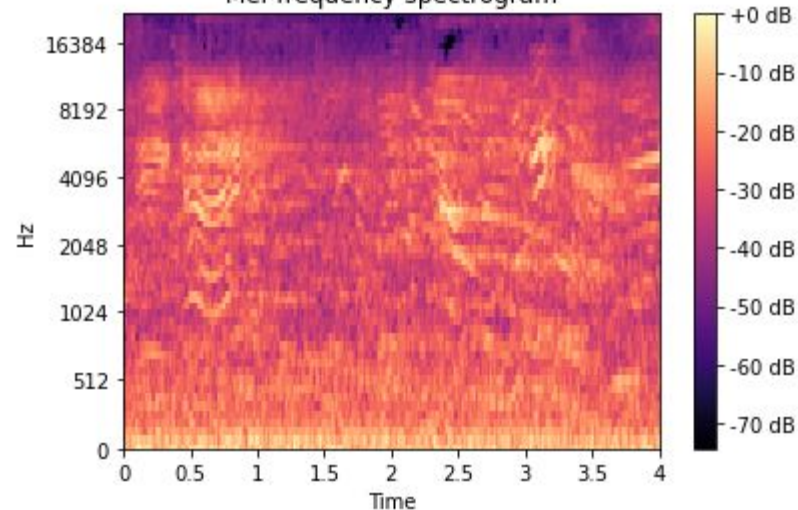
Original, mono



Restored from melspectrogram, mono

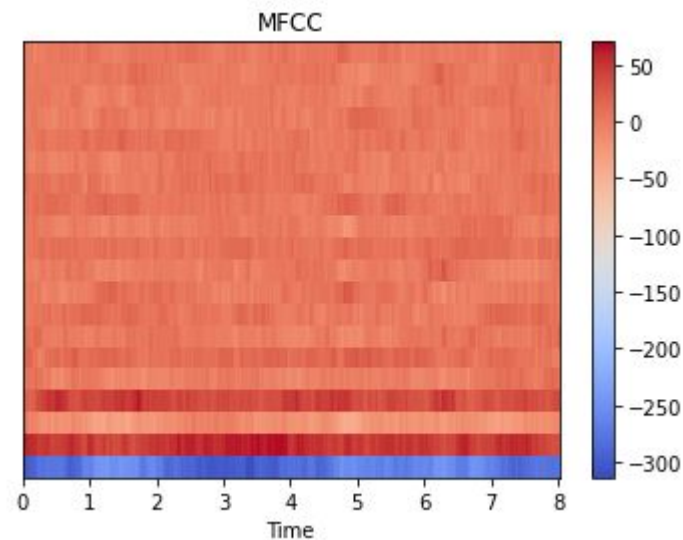
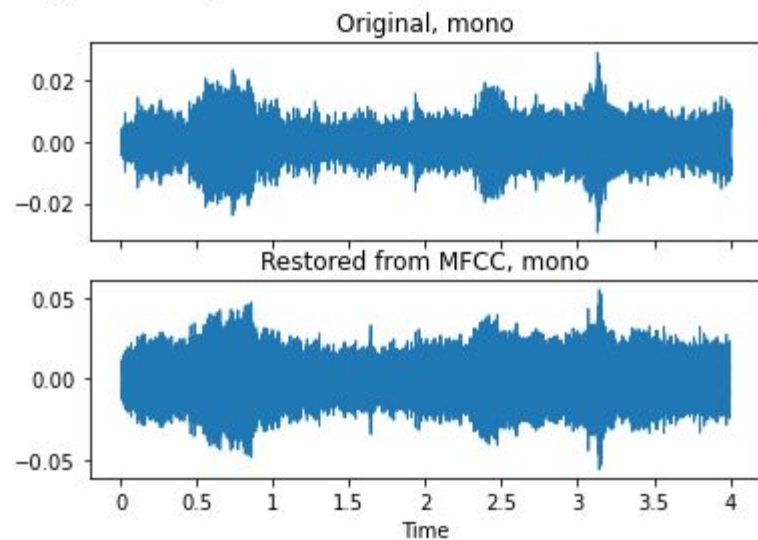


Mel-frequency spectrogram



MFCC analysis

original memory use = 176400, MFCC = 6900



Mini-Conclusion, based on applying methods to signal

- If one wants to use MFCC as a input for neural network against Mel-Spectrogram, s/he wins approximately **4x** in space (usually it is an input for the first convolutional layer)
- Nobody uses raw data for the input in the latest researches, as it seems hard for a neural network extract features from such an input
- each of methods have information lost after its application

Evaluating feature extraction of two methods: MFCC vs Mel-Spectrogram – Results

For a particular Urban8k classification task MFCC performs better ($0.77 > 0.65$) (accuracy scores)

It is useful to use MFCC instead of Mel-Spectrogram for a Neural Network to be able to increase the batch size if one wants a fast training

Research conclusion

- Mel-Spectrogram is commonly used for NLP, Transformers
- MFCC is commonly used for Reinforcement Learning, Hidden Markov Processes (when we care about memory)
- It is better to try both methods of pre-processing data for Neural Network, and then take the better.

Possible ways of future research:

- a. As images can be represented, as signals, try to use Mel-Spectrogram or MFCC for its feature extraction
- b. Train more specific architectures to explore more applications of these methods