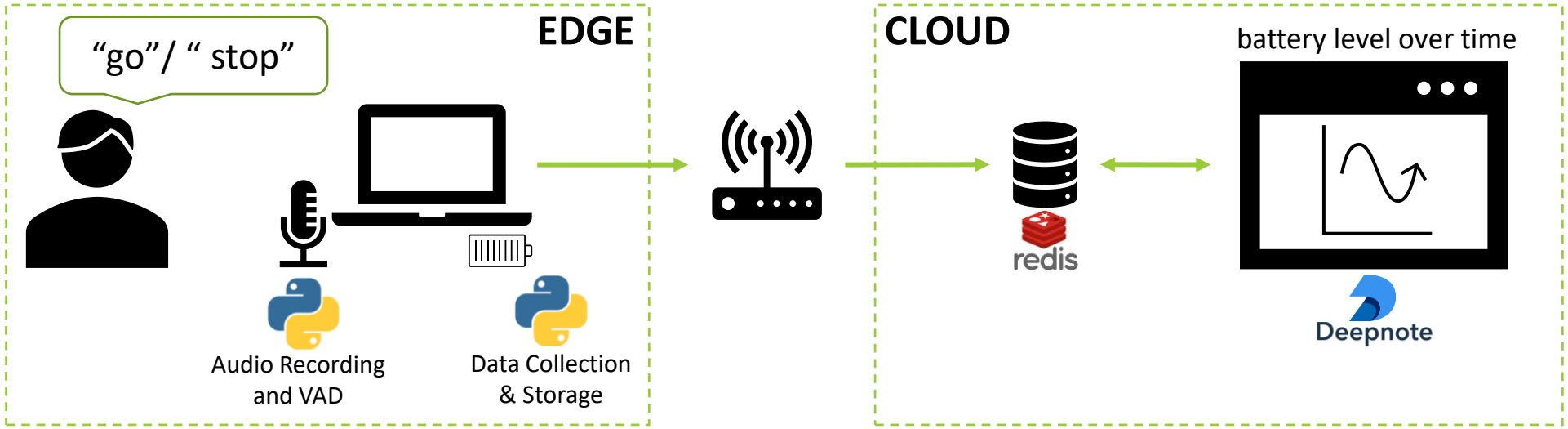
Machine Learning for IoT

LAB2: Pre-processing

LAB1-2: Smart Battery Monitoring (Simplified)



LAB2 Content

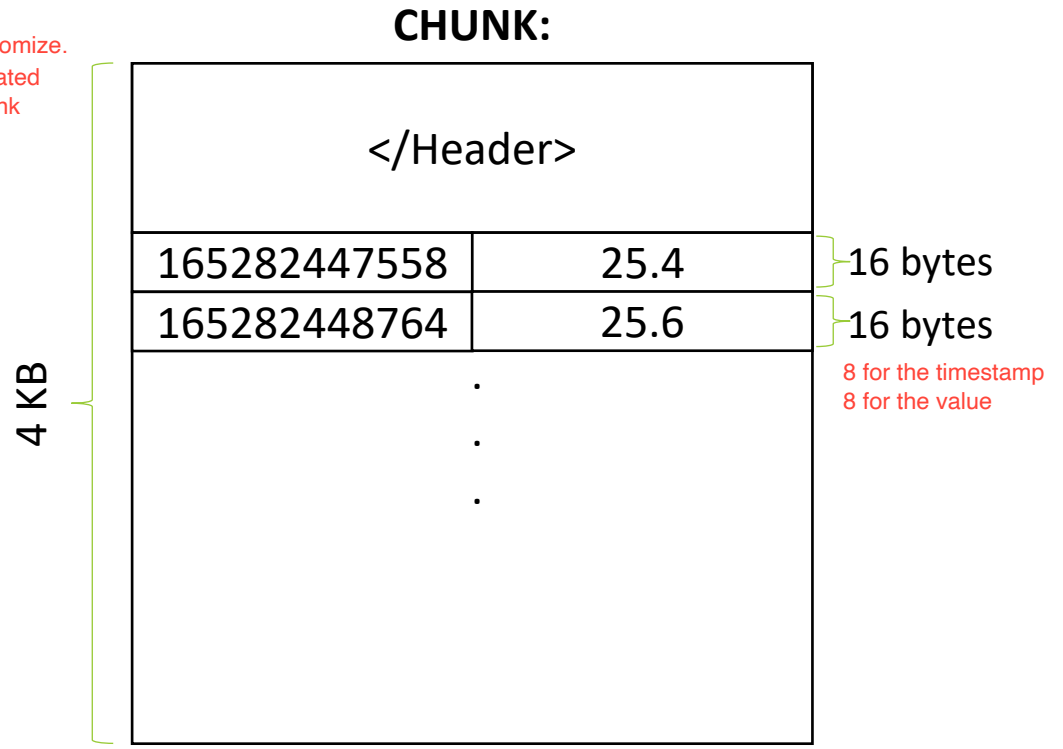
- Timeseries Processing:
  - Compression
  - Retention
  - Aggregation
- Audio Processing:
  - Resampling
  - Discrete Fourier Transform
  - Short-Time Fourier Transform
  - Mel Spectrogram
  - Mel-Frequency Cepstral Coefficients

Timeseries Processing

Redis TimeSeries Memory Model

- A Redis TimeSeries consists of a list of linked chunks
- Each chunk contains
  - Header
    - Information needed by Redis to manage the data
  - A set of Records
    - Each record consists of:
      - Timestamp: 64-bit (8 bytes)
      - Value: 64-bit (8 bytes)
- Chunk size is set when creating the TimeSeries
  - Default: 4 KB
  - Smaller → Less Memory, Slower Read/Write
  - Larger → More Memory, Faster Read/Write

a chunk is a part of memory with a fixed size that you can customize.
when you finish the memory in the chunk another chunk is created
but the side effect is that we do not have data in the same chunk



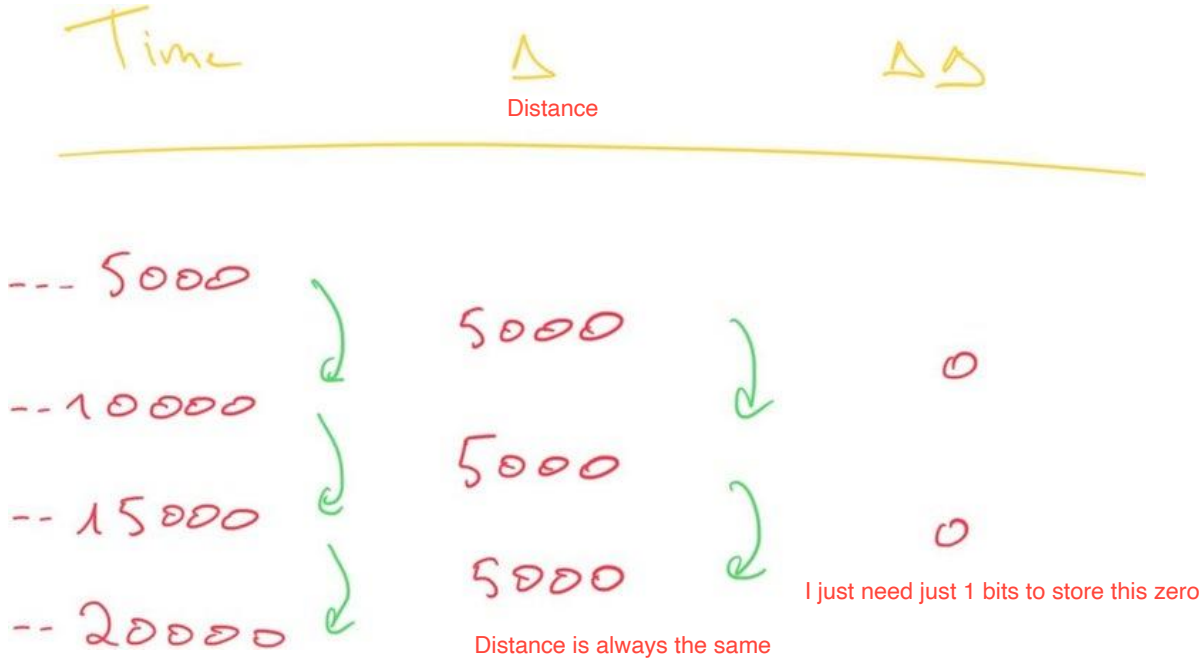
TimeSeries Compression

- Lossless compression
  - Gorilla algorithm

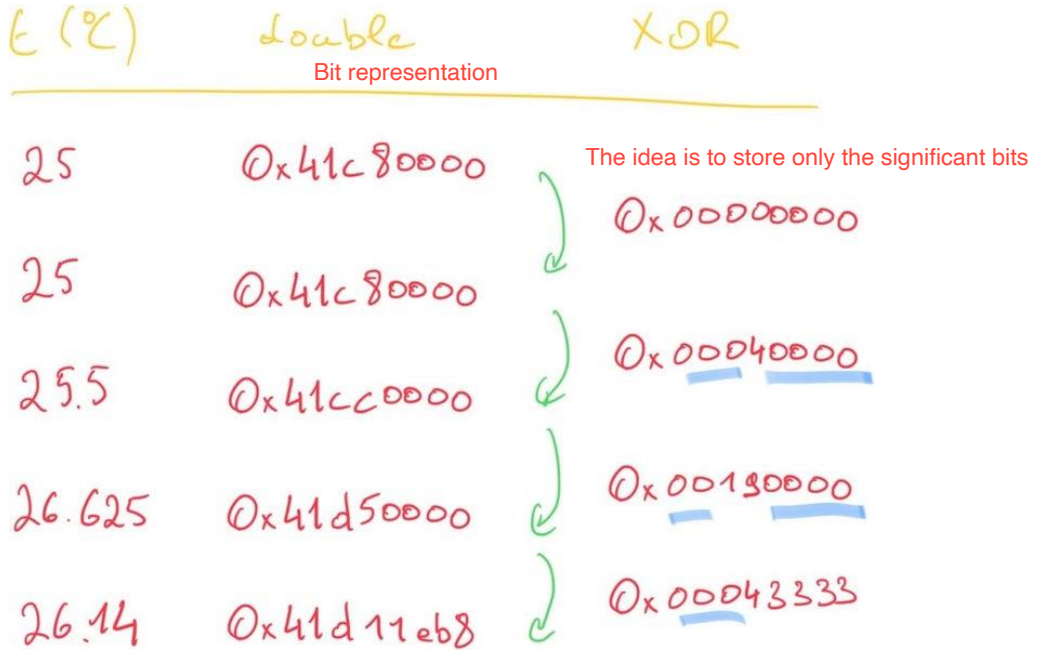
This is used for the time series and it is applied both for timestamp and for values and an example is the Zip Compression

Another kind of compression is the LOSSY compression.

Timestamp Compression:



Value Compression:



TimeSeries Compression

- Lossless compression
  - Gorilla algorithm
- Memory savings:
  - Depends on data
    - Best-case: 98.4%
    - Worst-case: 113.3%
      - Memory increases! But rare.
    - Average-case: 90.0%
- Compression improves performance due to a lower number of memory accesses

- **Note:** Compression is active by default

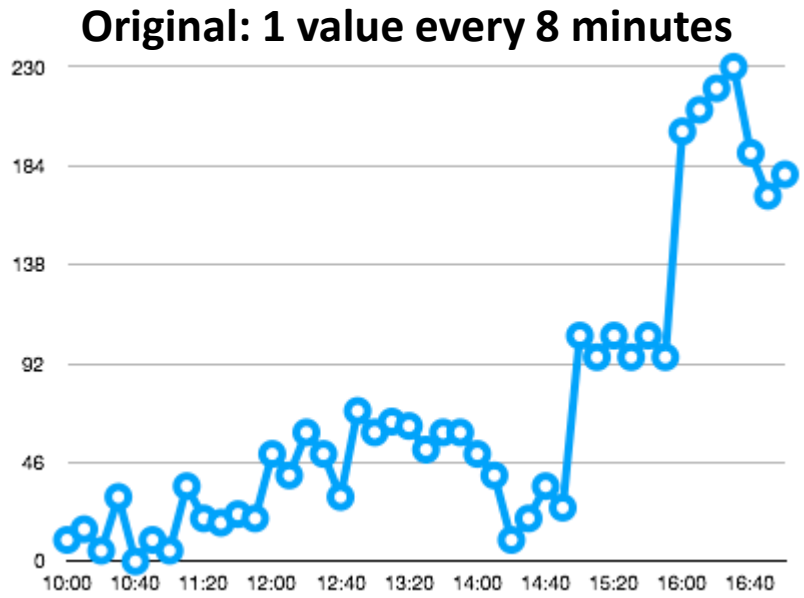
Example

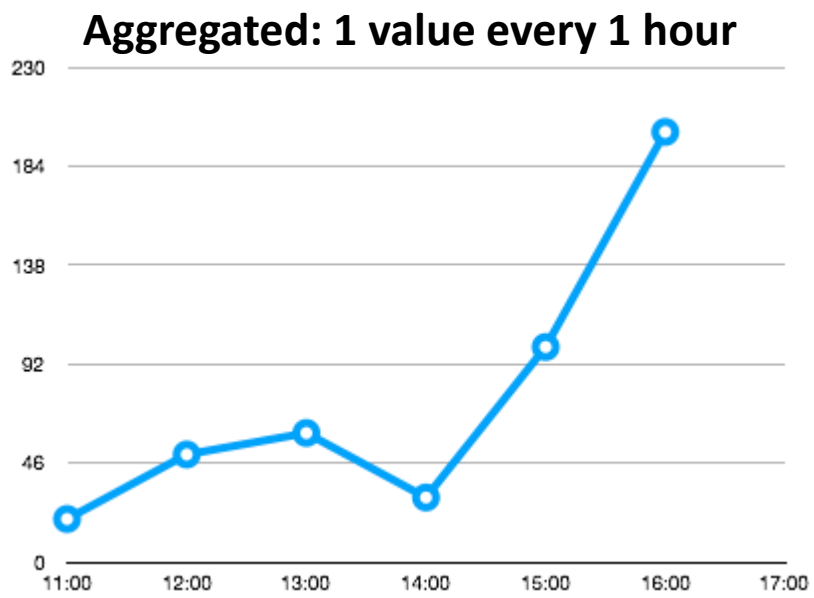
- Which is the memory usage to store temperature every 5 seconds after 1 month?
  - 1 month = 30 days * 24 hours * 60 minutes * 60 seconds = 2592000 seconds
  - # of records = 2592000 / 5 = 518400
    in a chunk
  - Uncompressed Memory ≈ 518400 * 16 bytes = 8294400 bytes = 7.910 MB
  - Compressed Memory ≈ 7.910 MB - 90% = 0.791 MB

  - Approximations:
    - We neglected the header size
    - We neglected that the memory usage is always a multiple of the chunk size
    - We considered the average compression ratio

TimeSeries Aggregation

- Lossy Compression
- Aggregation Parameters:
  - Bucket Duration
  - Aggregation type: avg, sum, min, max, range, count, first, last.
- **Note:** Aggregation never changes the original timeseries but creates a new one





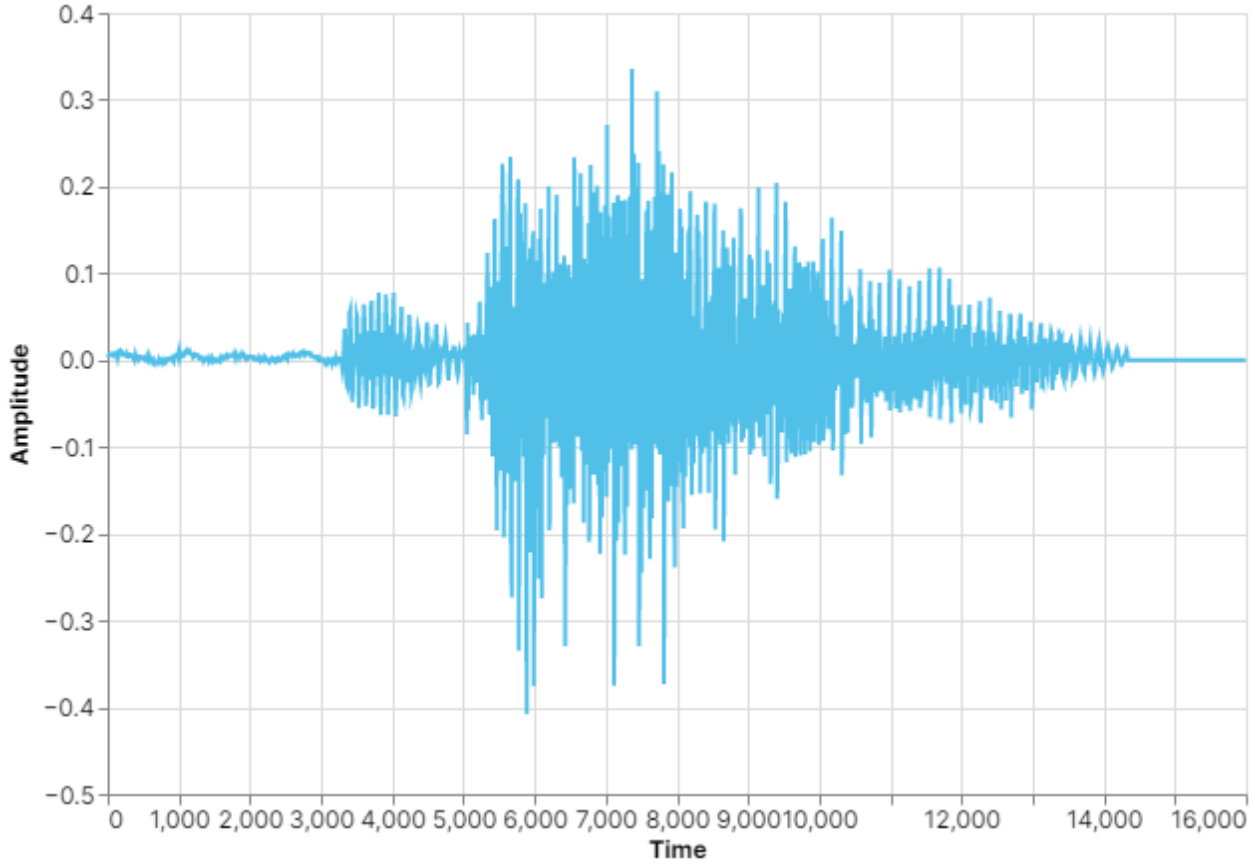
TimeSeries Retention

- You can prevent your timeseries growing indefinitely by setting a maximum age for samples compared to the last event time (in milliseconds).
- By default, retention is 0
  - i.e., the timeseries will be never trimmed

Audio Processing

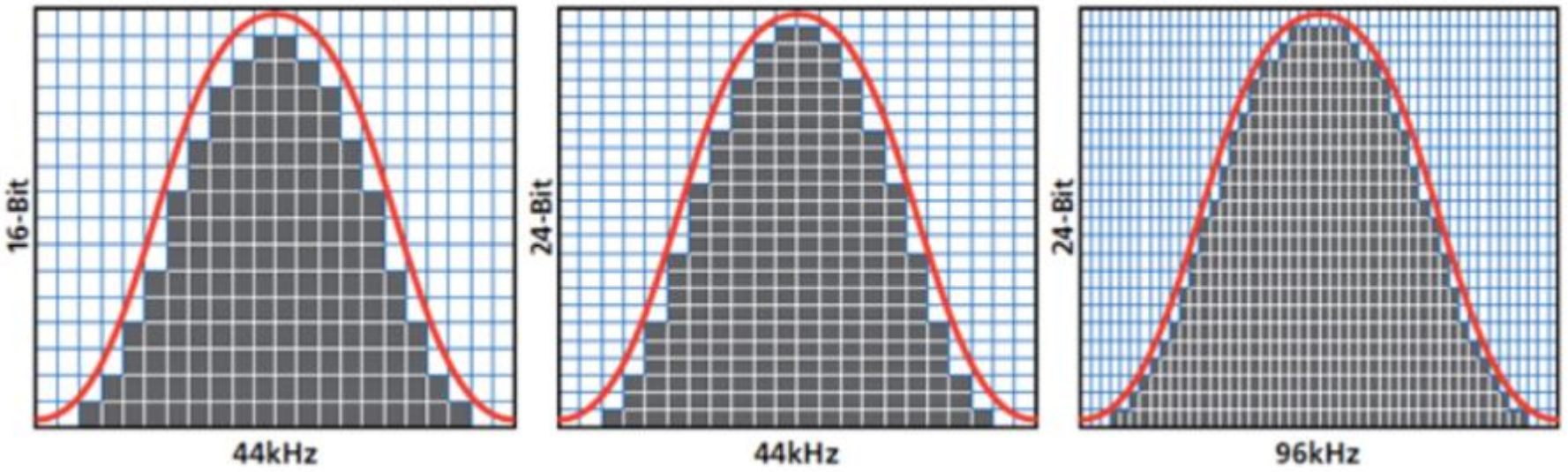
Waveform

- Speech signals are defined as pressure variations travelling through the air
- The waveform represents how the relative air pressure varies over time



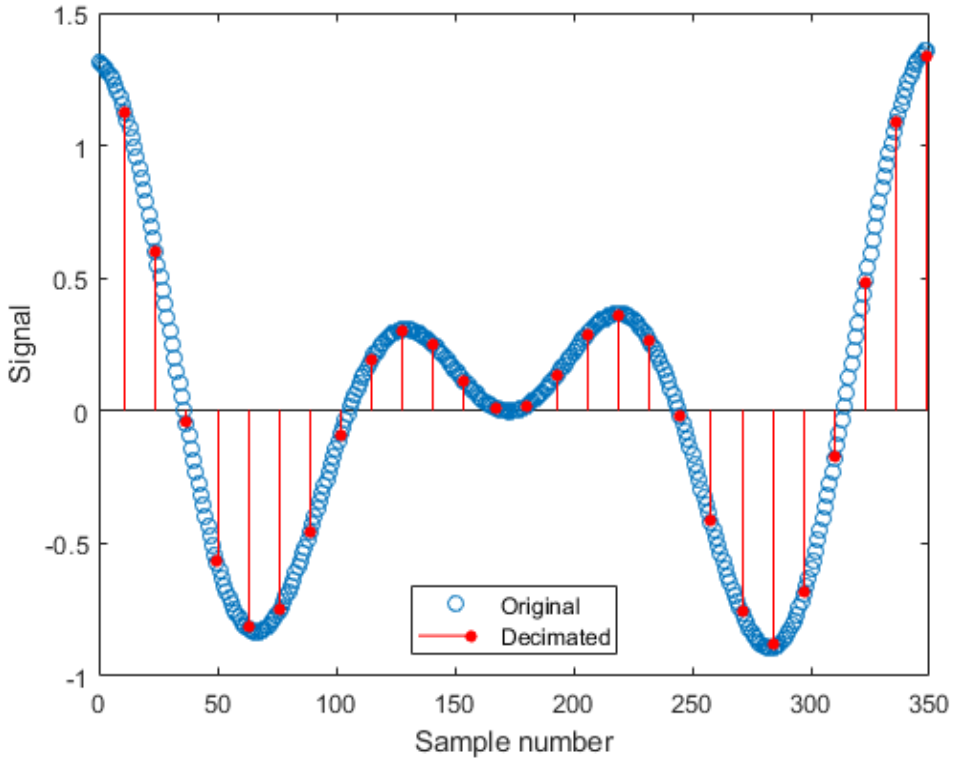
Waveform

- The “quality” of the waveform depends on:
  - Resolution
    - E.g., int16 (2 bytes), int24 (3 bytes), int32 (4 bytes)
  - Sampling Frequency
    - E.g., 48 kHz, 44.1 kHz, 16 kHz, …



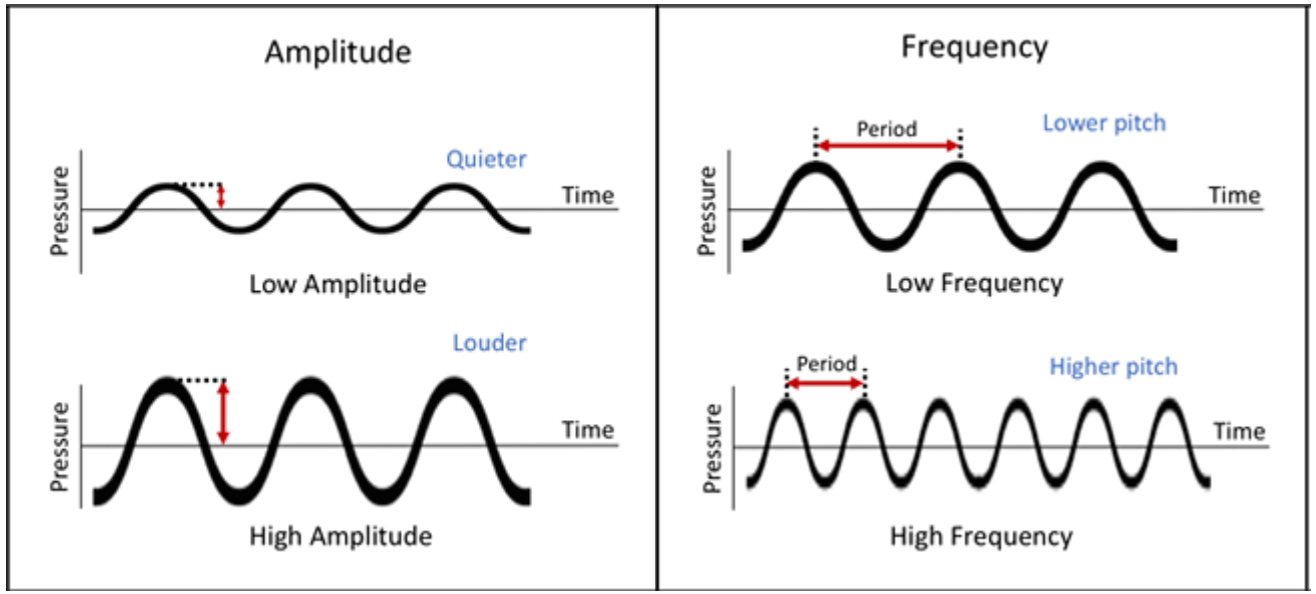
Resampling

- Downsample the signal from higher frequency to lower frequency



Waveform Properties

- Volume
  - Amplitude over time
  - Higher volume → louder
- Pitch
  - Related to frequency
  - Higher frequency → Higher sound



Audio Features

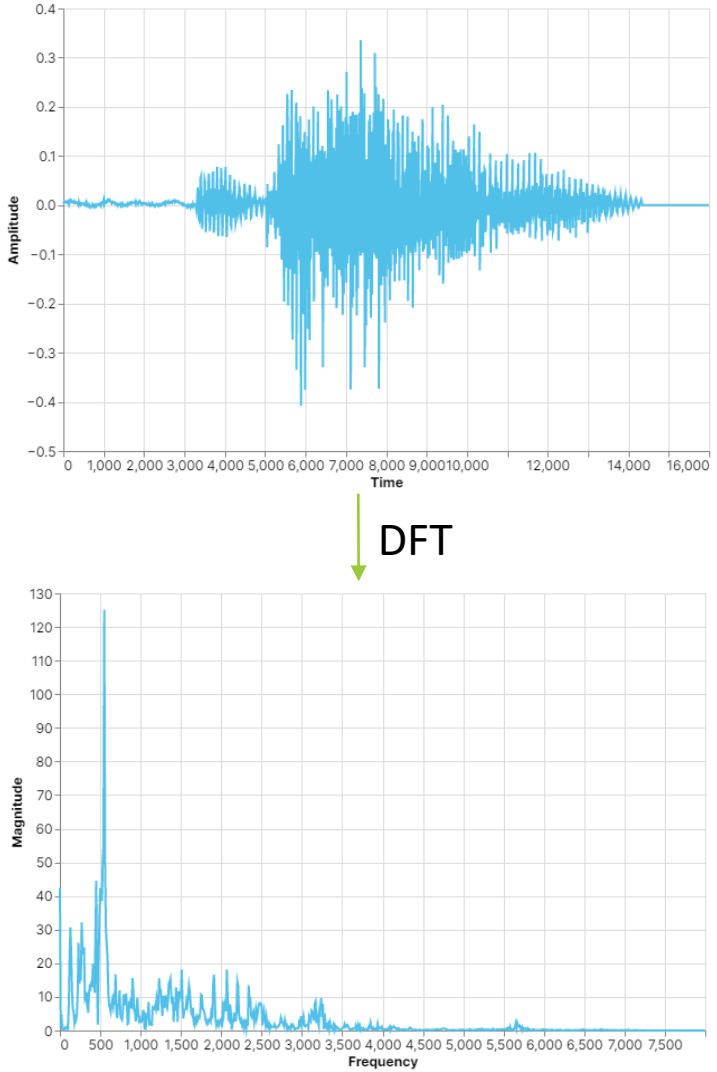
- Time domain
- Frequency domain
- Time-Frequency domain

Discrete Fourier Transform

- Time Domain x_n → Frequency Domain X_k
  - Compute this transformation for finite # frequencies
- DFT:

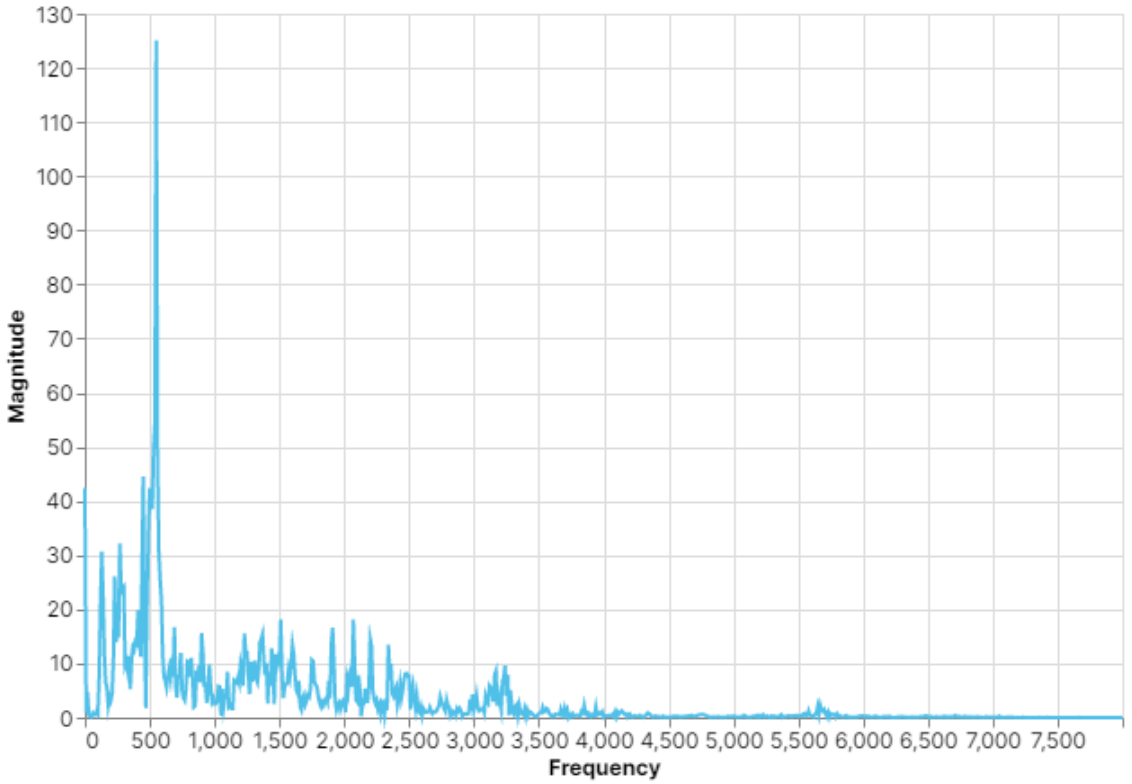
$$X_k = \sum_{n=0}^{N-1} x_n \, e^{i2\pi \frac{kn}{N}}$$

- # frequency = # samples = *N*
  - Invertible transformation
  - Computational efficient



Redundancy in the DFT

- Output:
  - Array of shape: (N/2 + 1)
- The DFT is symmetric w.r.t. the Nyquist Frequency
- Example:
  - 1s at 16 kHz → # samples = 16000
  - Output shape: (8001)



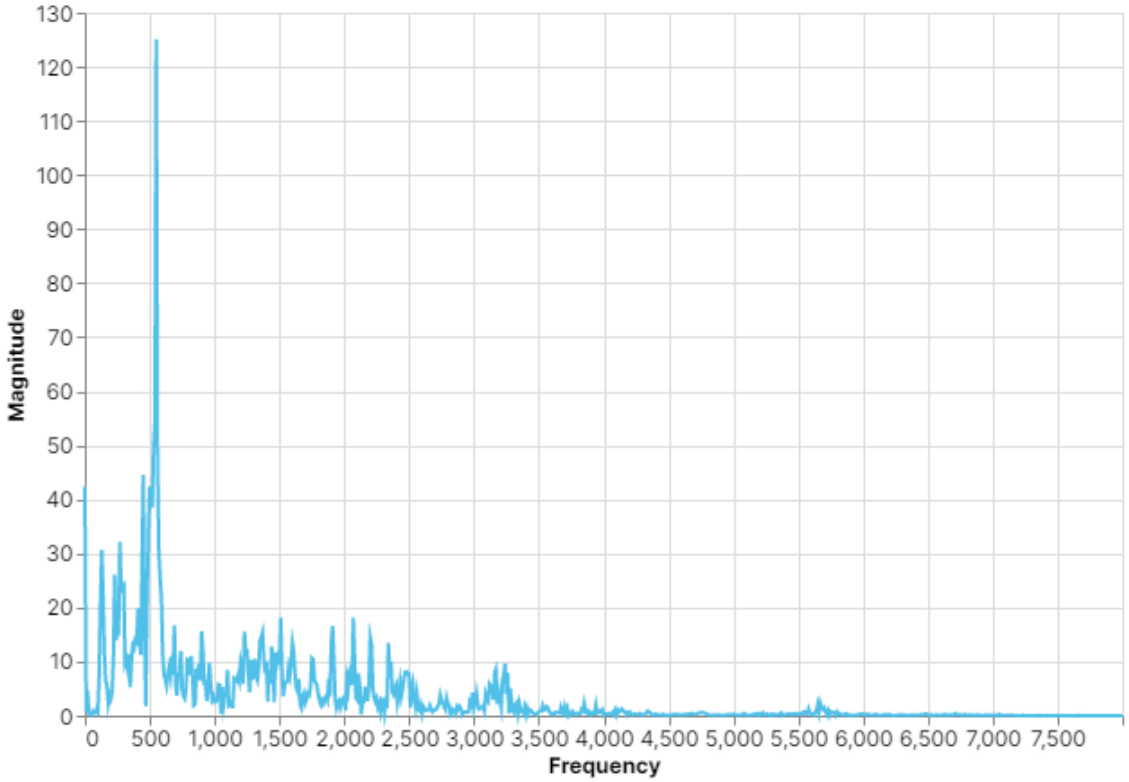
From DFT to FFT

- DFT is computationally expensive (N^2)
- FFT is a more efficient implementation of DFT ($Nlog_2N$)
  - FFT works when N is a power of 2

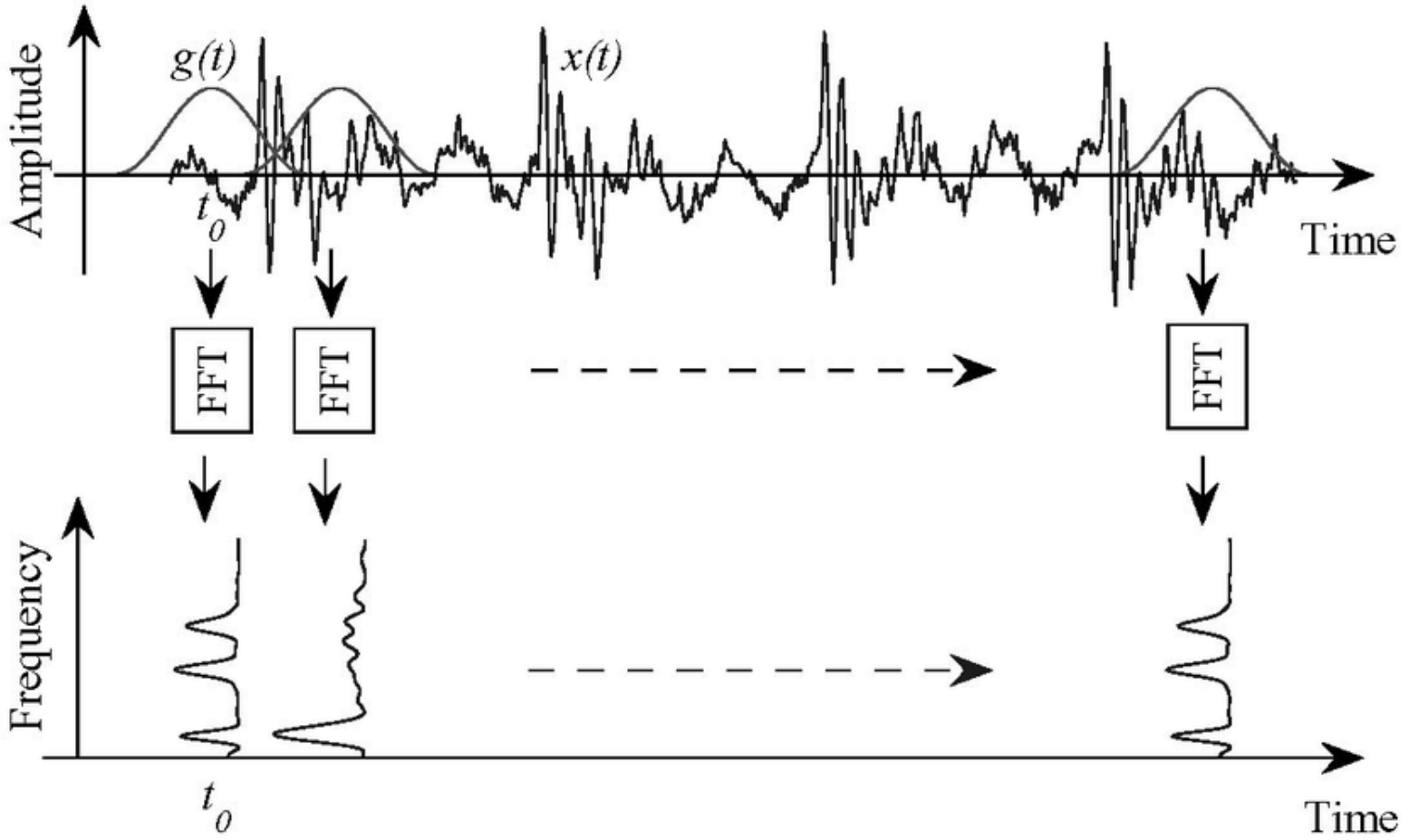
DFT Limitation

- Speech signals are not stationary
  - The DFT is the average of all the phonemes in a word
  - NO time information
- Problem: we need to understand
  - WHICH phonemes are in the word → frequency
  - WHEN phonemes appear in the word → time

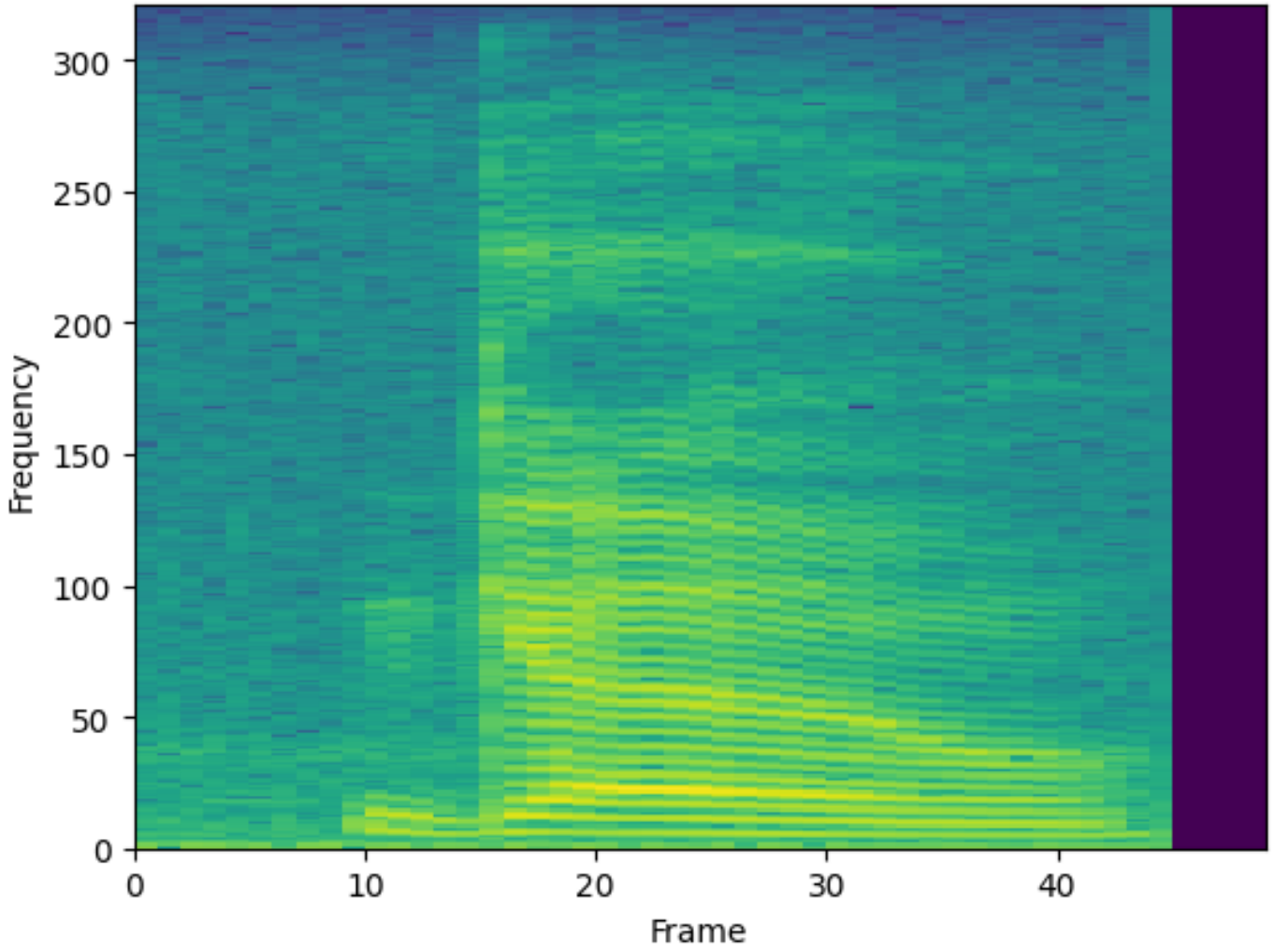
→Time-Frequency Domain



Short-Time Fourier Transform (STFT)

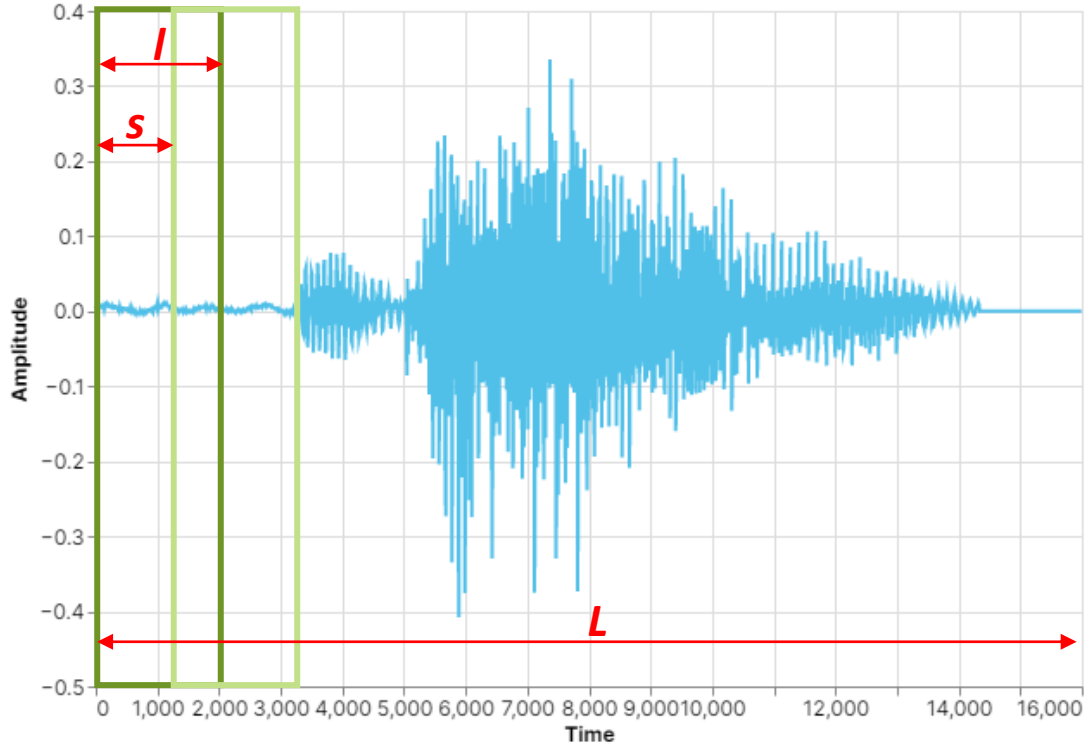


STFT Visualization



STFT parameters

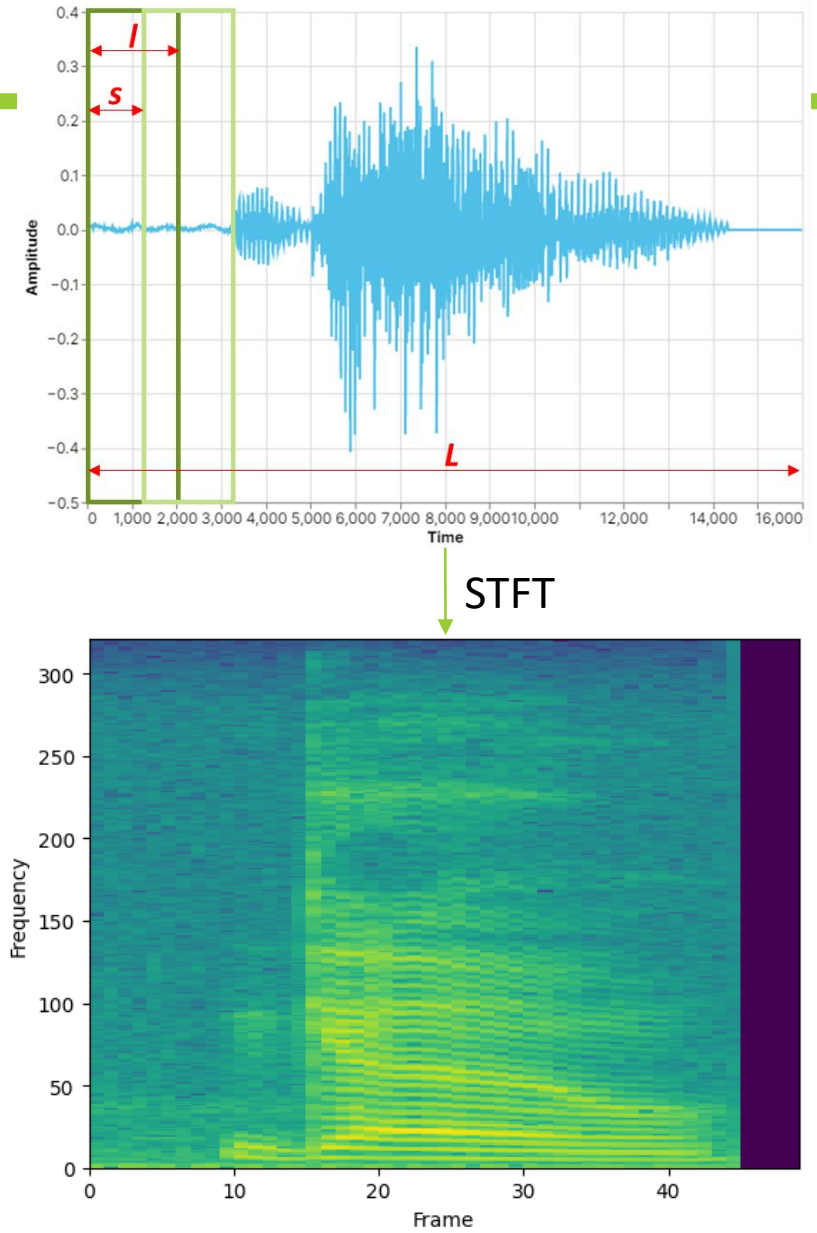
- Frame Length *l*
- Frame step *s*
  - Also defined as percentage of overlap between two consecutive frames
- FFT Length
  - Commonly set equal to *l*



STFT Output: Spectrogram

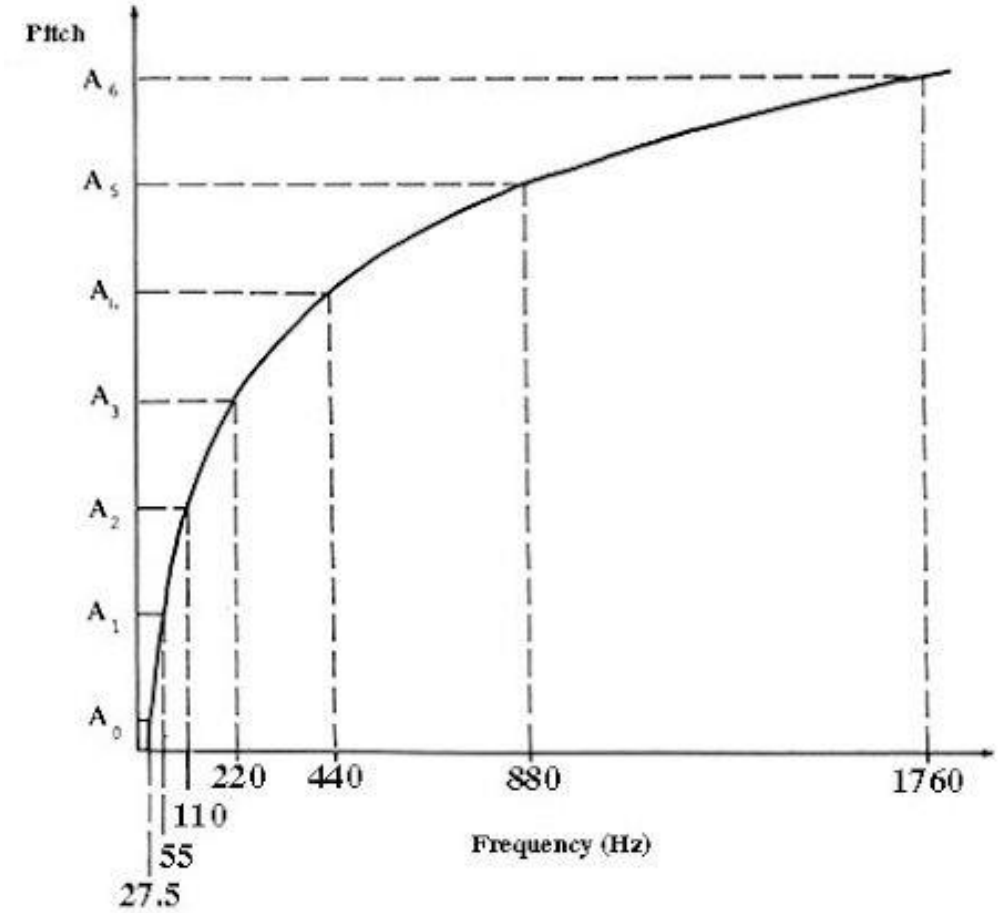
- 2D Matrix of shape:
  - (# frequency bins, # frames) = (l / 2 + 1, (L – l) / s + 1)
- Example:
  - L = 1 s (@16 kHz), l = 40 ms, s = 20 ms
  - # Frequency bins:

    (40 ms * 16 kHz) / 2 + 1 = 321
  - # Frames:
    - (16000 – 40 ms * 16 kHz) / (20 ms * 16 kHz) + 1 = 49



STFT Limitation

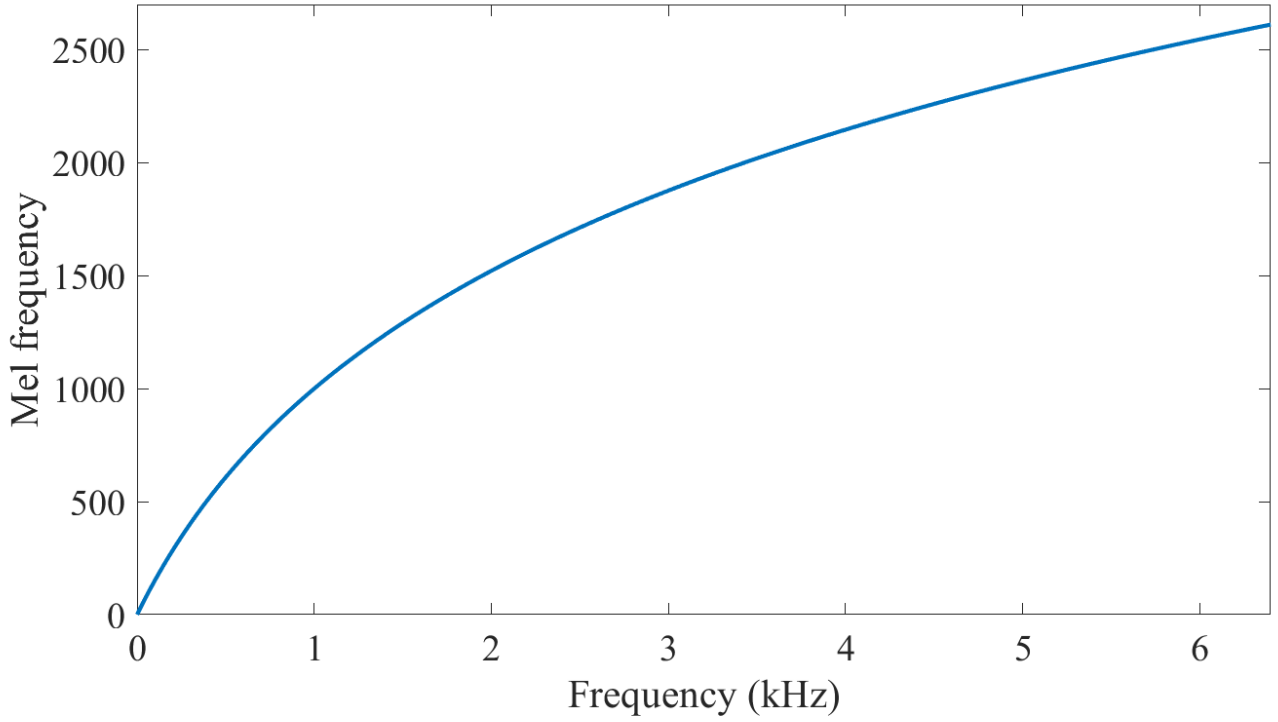
- Pitch:
  - 2 frequencies are perceived similarly if they differ by a power of 2



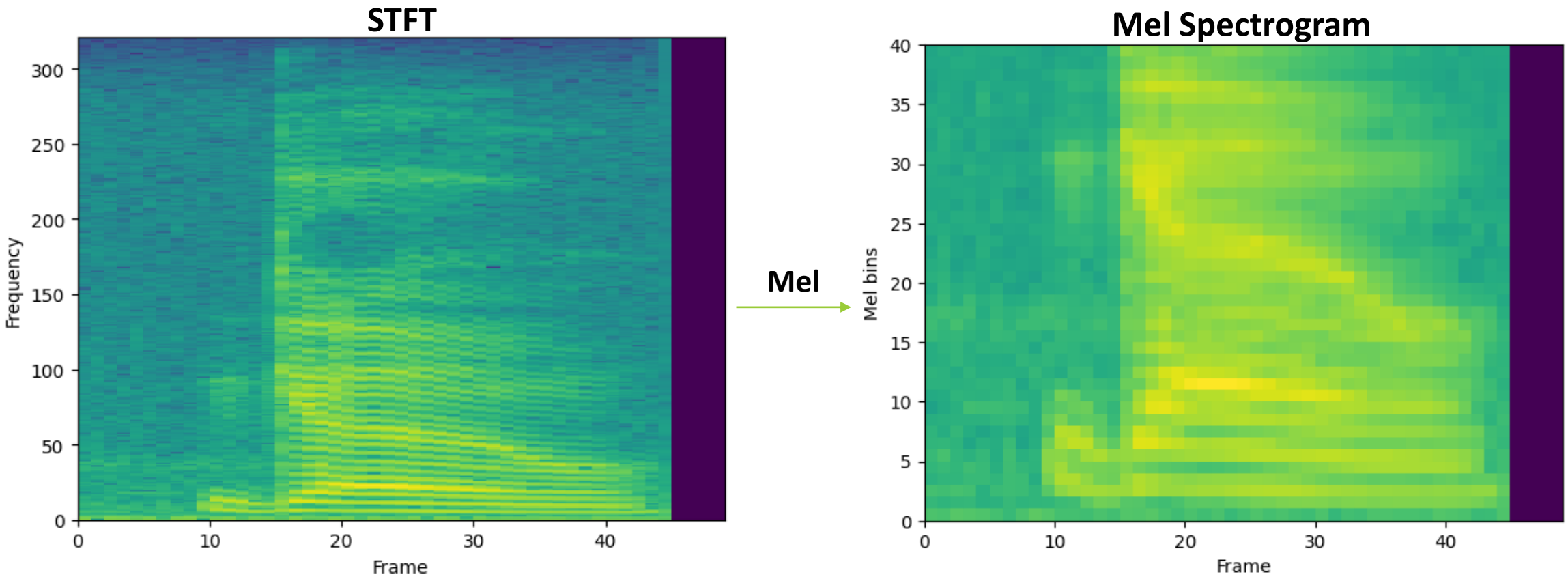
Mel scale

- Frequency-to-Mel transform:

$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right)$$

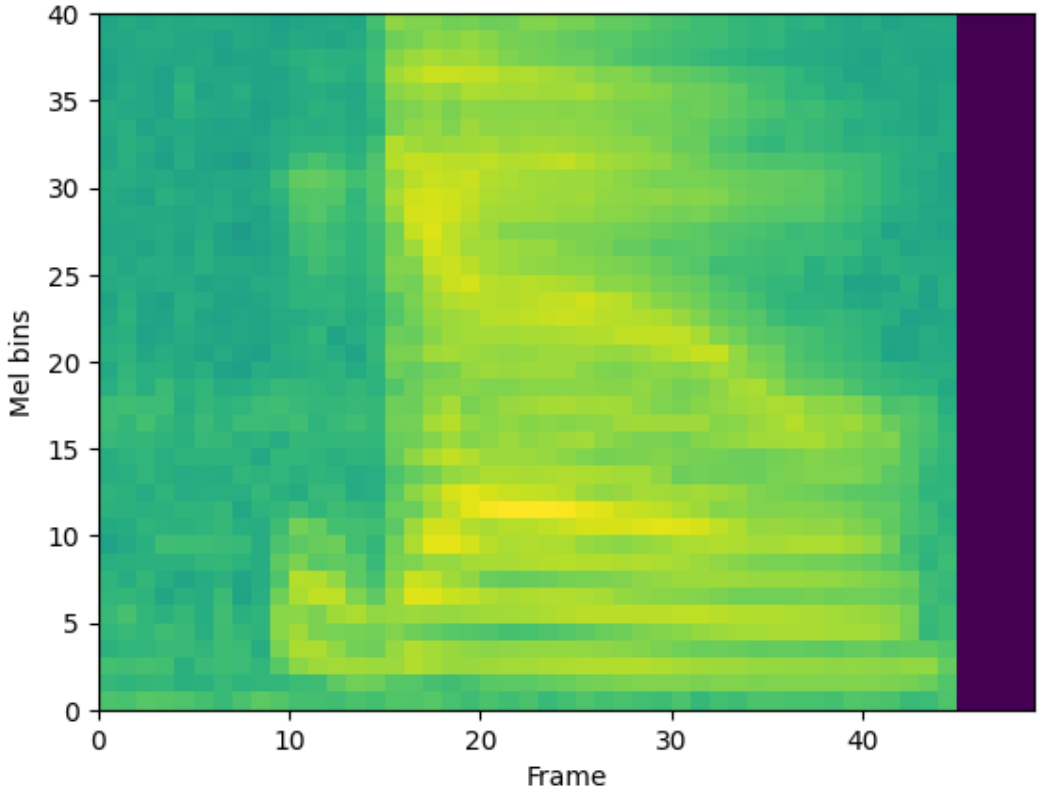


Mel Spectrogram



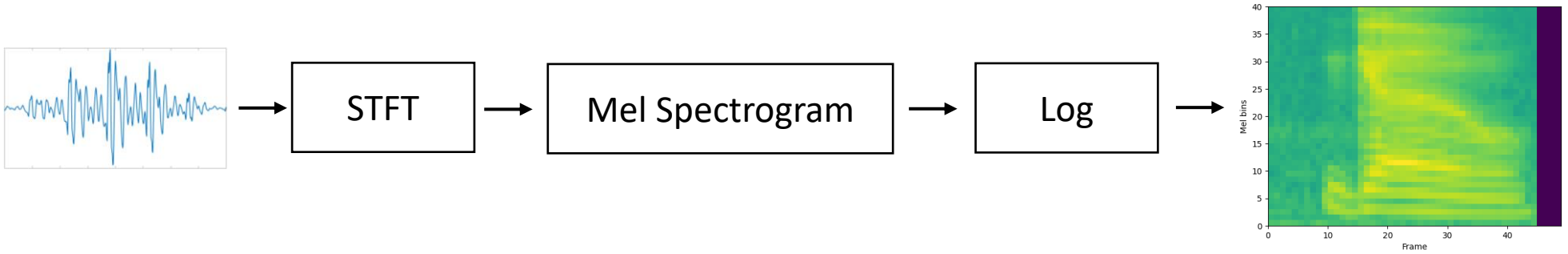
Mel Spectrogram

- Parameters:
  - Lower Frequency (in Hz)
  - Upper Frequency (in Hz)
  - # of Mel Frequency Bins
- Output:
  - 2D Matrix of shape:
    - (# Mel frequency bins, # frames)
- Example:
  - Lower Frequency: 20 Hz
  - Upper Frequency: 4000 Hz
  - # of Mel Frequency Bins: 40

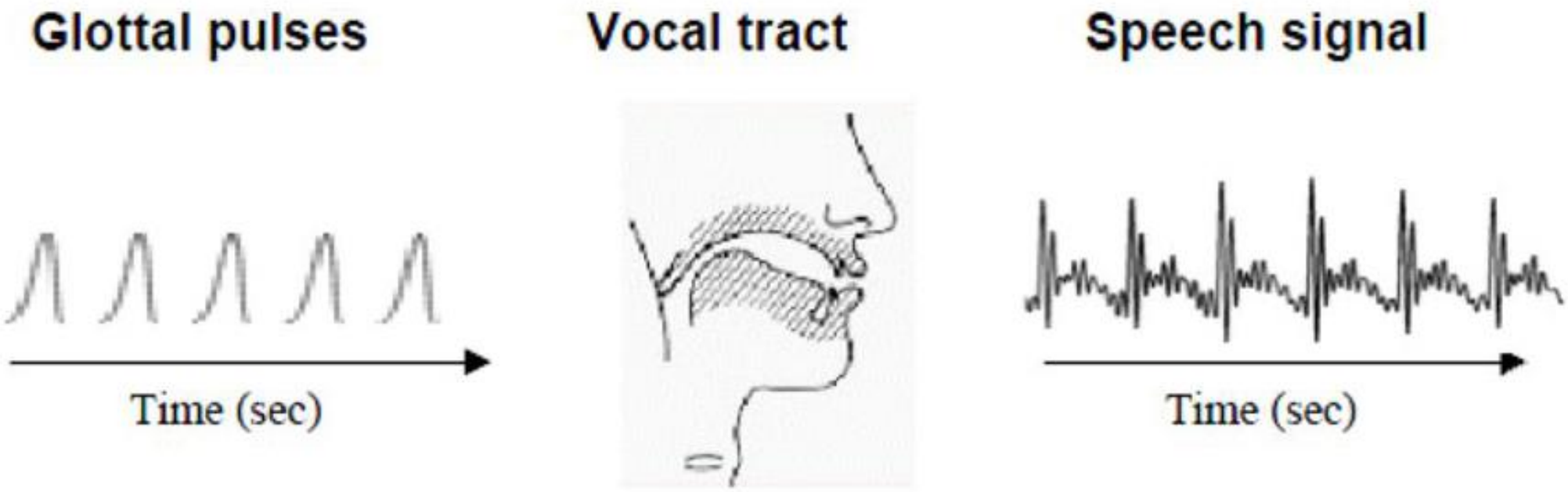


Log-Amplitude Mel Spectrogram

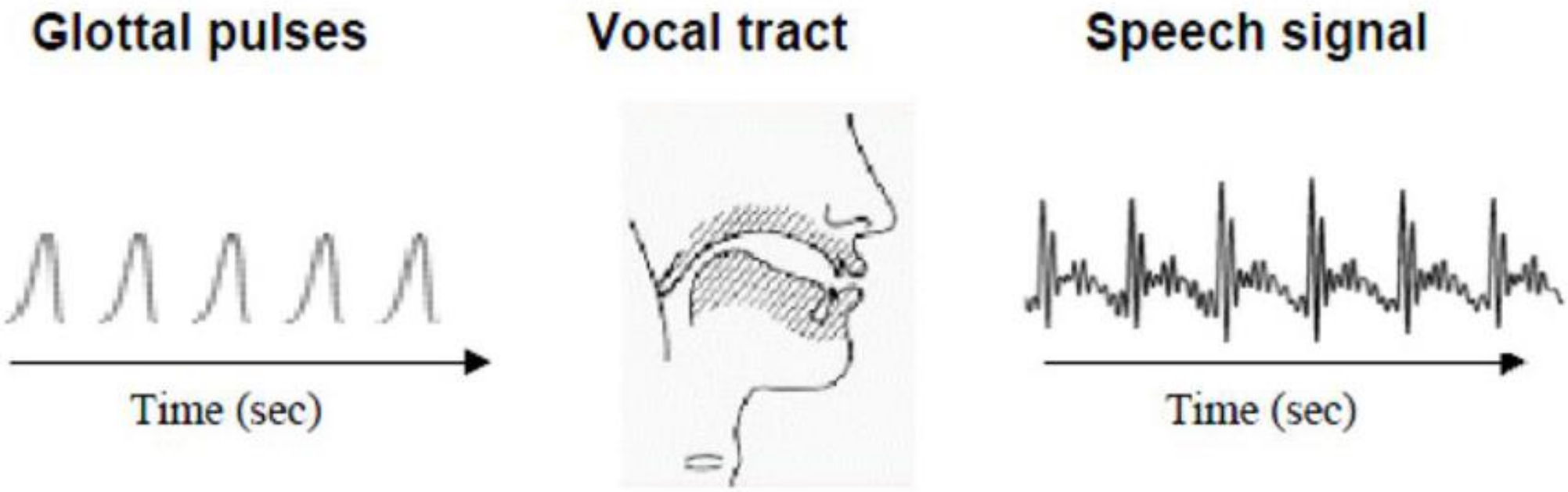
- Our perception of loudness is logarithmic
  - Apply logarithm on the amplitude of the spectrum



Speech generation

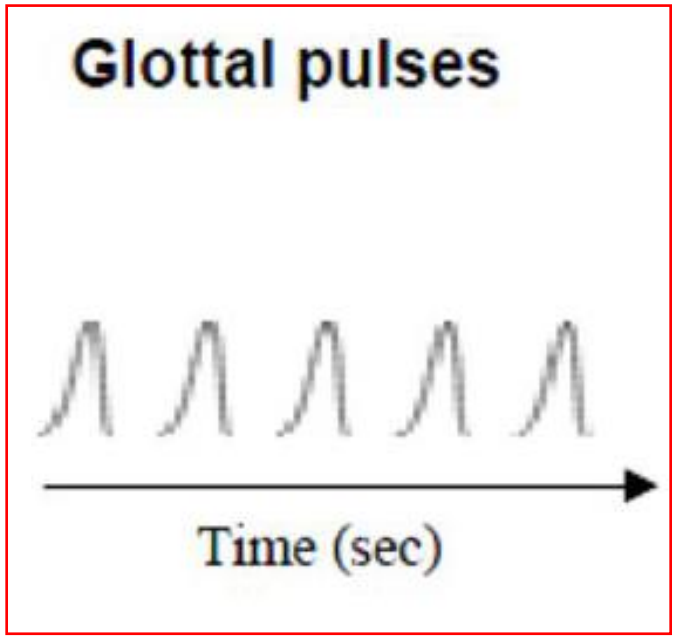


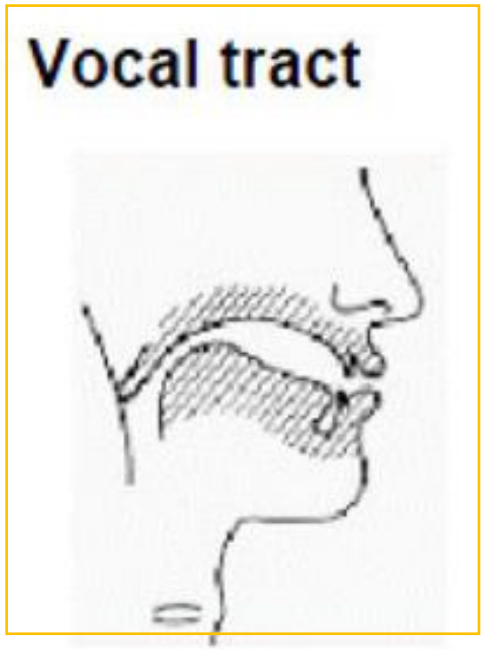
Speech generation

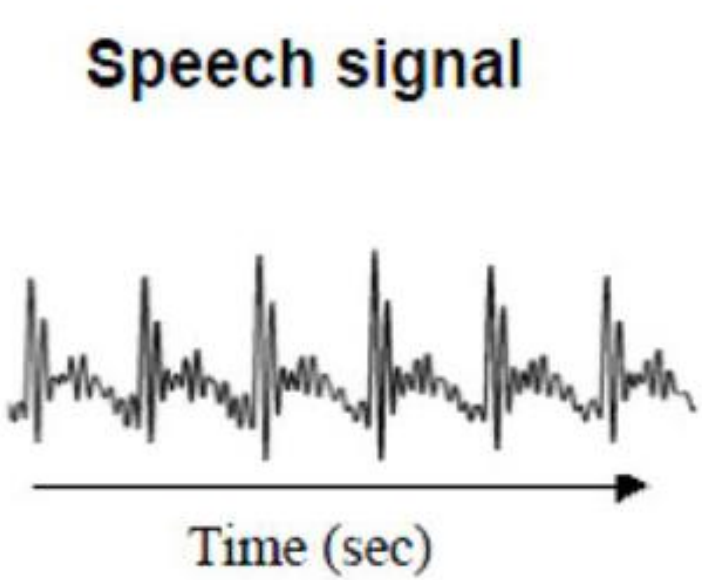


$$X(t) = E(t) + H(t)$$

Speech generation





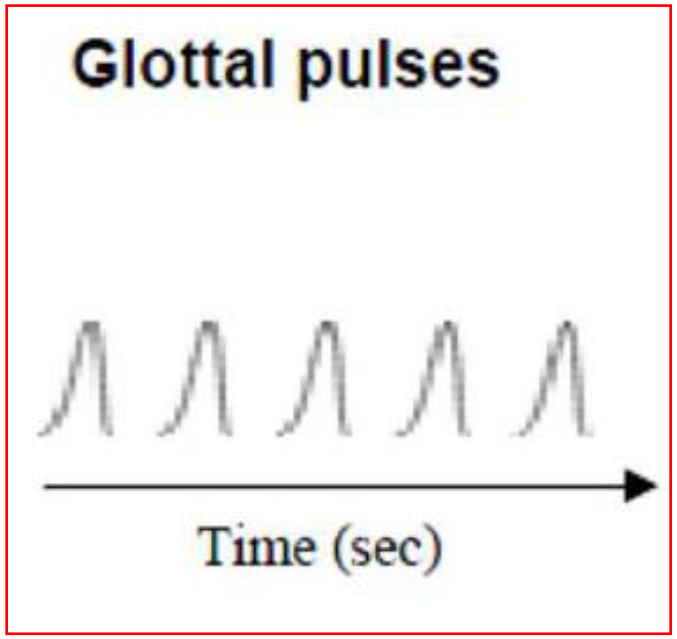


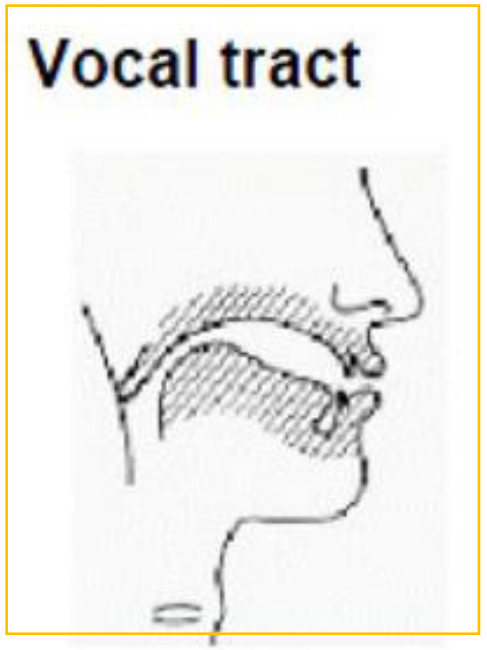
$$X(t) = E(t) + H(t)$$

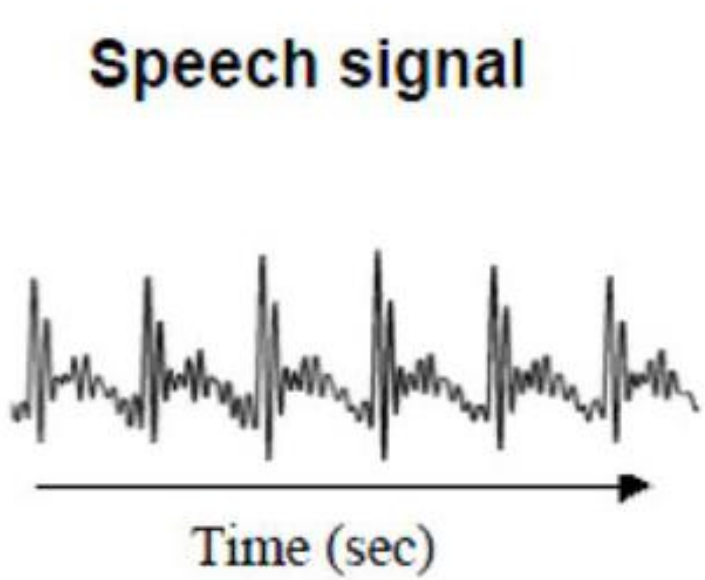
Glottal Pulses

Spectral Envelope

Speech generation







$$X(t) = E(t) + H(t)$$

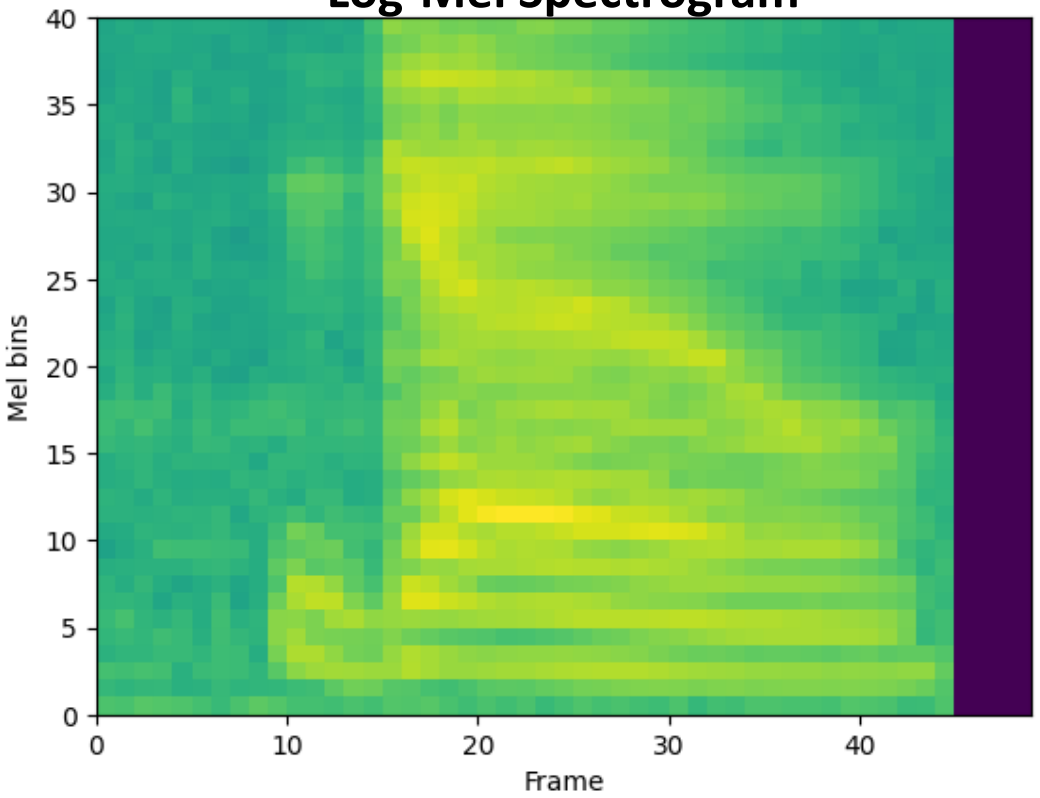
Glottal Pulses

Cepstrum

Spectral Envelope

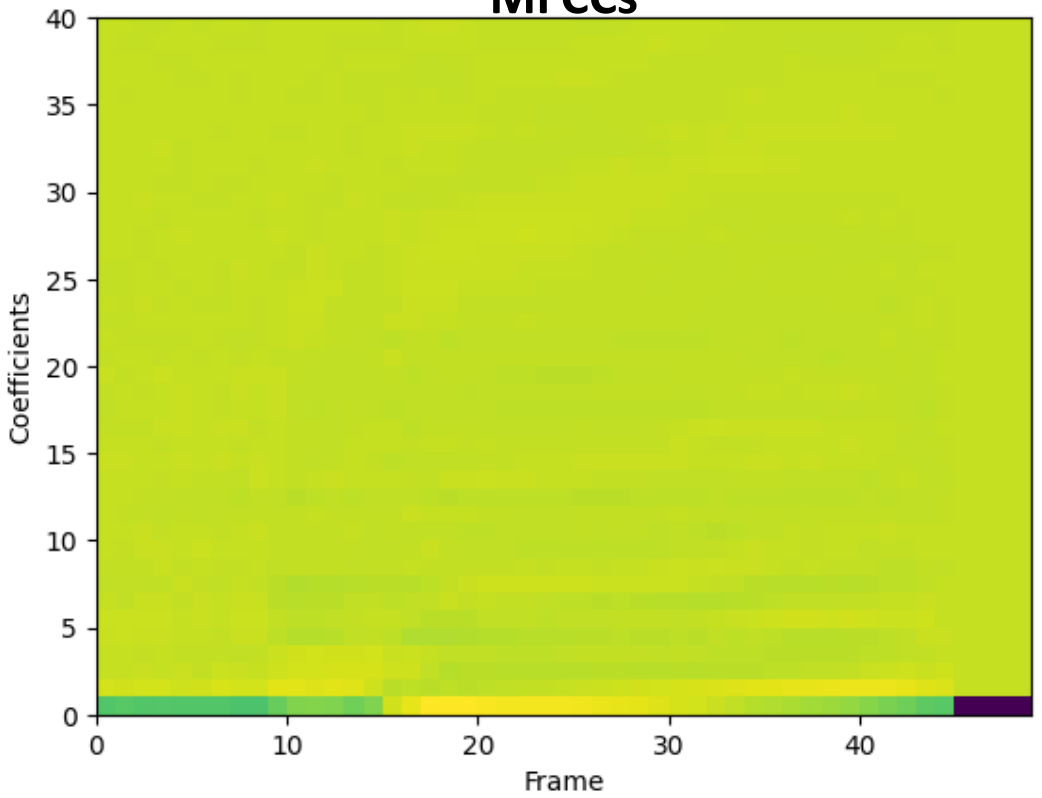
Mel Frequency Cepstral Coefficients (MFCCs)

Log-Mel Spectrogram



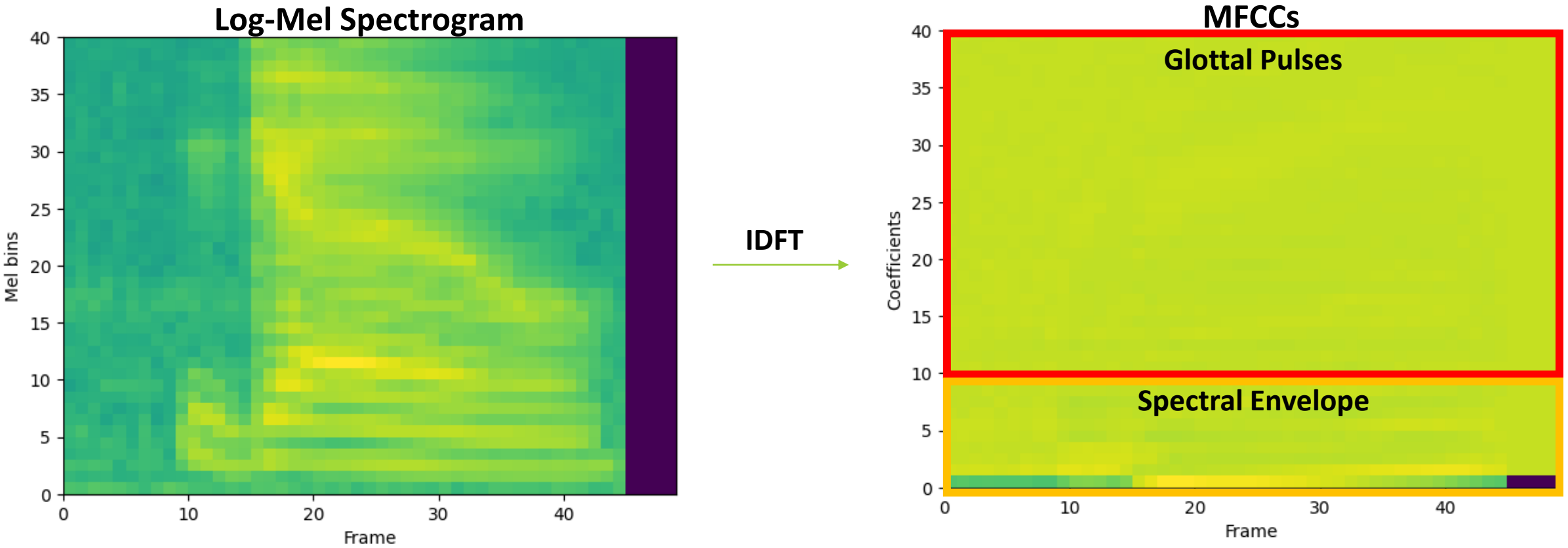
IDFT

MFCCs



Spectrum → Cepstrum

Mel Frequency Cepstral Coefficients (MFCCs)



Which features for training?

- Speed vs. Quality tradeoff