<u>DL</u> in Audio: Sound and Sound Representations

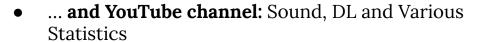


2024
Deep Learning in Audio Processing,
Invited Talks

Maksim Kaledin

About

- **PhD in Applied Mathematics:** With the topic about RL and optimal control
- **Currently:** Associate Professor, Department of Big Data and Information Retrieval
- Sound Research for Some Time: Key topic is audio source separation
- Btw, there is a course: DLA













A short history of Speech Recognition





In 1962, IBM introduced "**Shoebox**" which understood and responded to 16 words in English.

In **1952**, Bell Laboratories designed the "Audrey" system which could recognize a single voice speaking digits aloud





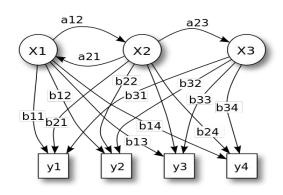


A short history of Speech Recognition



The '80s saw speech recognition vocabulary go from a few hundred words to **several thousand words** thanks to **HMM**

DARPA's system was capable of understanding over **1,000** words. **Siri** was a spin-out of DARPA development:)



A short history of Speech Recognition

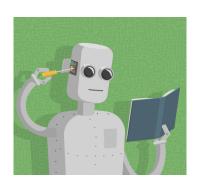


90,8

Speech recognition was propelled forward in the 90s in large part because of **faster processors**

And then came the era of big data, machine learning and GPUs





A short history of Speech Synthesis

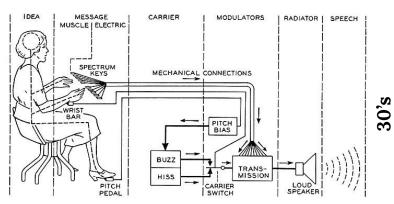
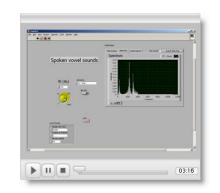


Fig. 8-Schematic circuit of the voder.

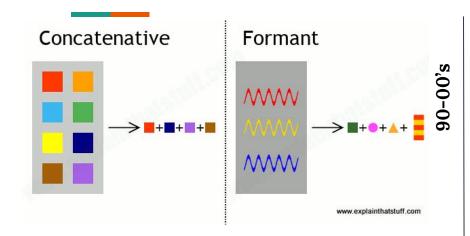
Formant-based on rules. You may listen examples in Atari&Sega games:)

until 80%

In **1939**, The Bell Laboratory's **Voder** was the first attempt to electronically synthesize human speech by breaking it down into its **acoustic components**



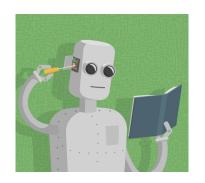
A short history of Speech Synthesis



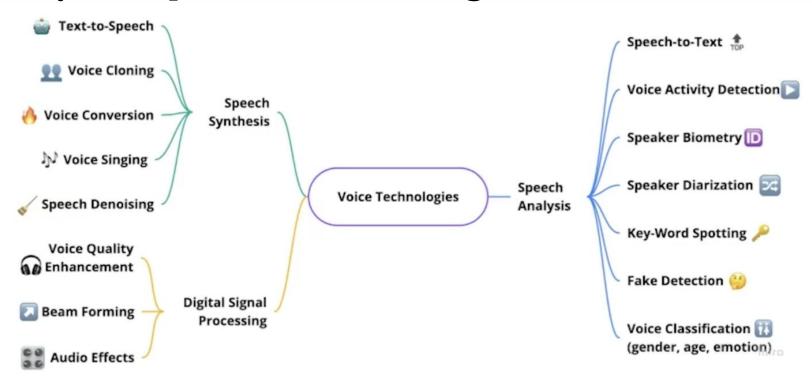
And then came the era of big data, machine learning and GPUs

Concatenative synthesis is a technique for synthesising sounds by concatenating short samples of recorded sound (called *units*).





Briefly on Speech Technologies

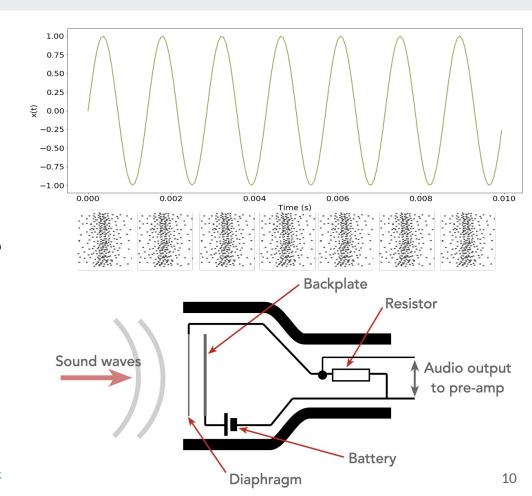


Sound representation

What is sound and how to store it in memory?

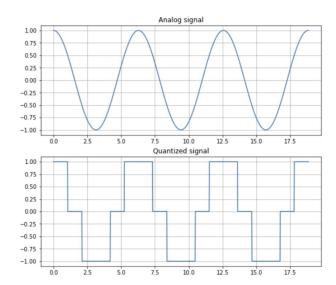
What is sound?

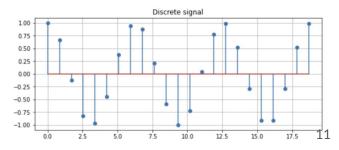
- **Sound wave** is the pattern of **oscillations** caused by the movement of energy traveling through the air
- Microphone picks up these air oscillations and converts them into electrical vibrations
- These oscillations are converted into an analog signal and then a digital signal



How is sound stored in the computer?

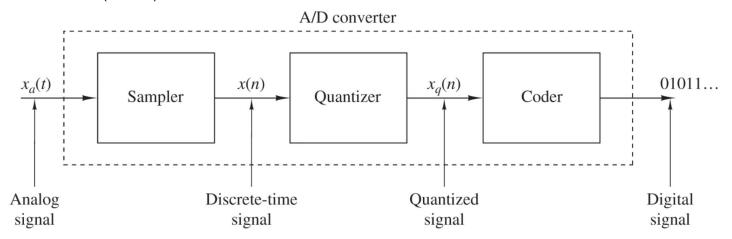
- The analog signal is discretized, quantized and encoded
- An analog signal is **discretized** in that the signal is represented as a sequence of values taken at discrete points in time **t** with step **d**
- Quantisation of a signal consists in splitting the range of signal values into N levels in increments of d and selecting for each reference the level that corresponds to it
- Signal **encoding** is just a way of presenting the signal in a more compact form





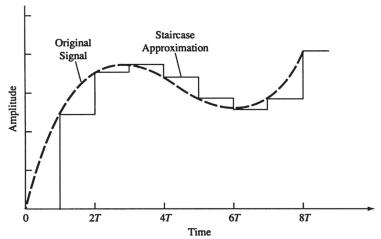
Analog-to-Digital Conversion

- Converting analog signals to a sequence of numbers having finite precision
- Corresponding devices are called A/D converters (ADCs)



Digital-to-Analog Conversion

- Process of converting a digital signal into an analog signal
- Interpolation
 - Connecting dots in a digital signal
 - Approximations: zero-order hold (staircase), linear, quadratic, and so on



What other characteristics are there?

- **Sample rate (SR)** number of audio samples per one second (e.g. 8 kHz, 22.05 kHz, 44.1 kHz)
- **Sample size** number of bits per one sample (e.g. 8, 16, 25, 32 bits)
- **Number of channels** -- how many signals we record in parallel (e.g. mono(1), stereo(2))

8000 Hz

The international $\underline{G.711}$ \square standard for audio used in telephony uses a sample rate of 8000 Hz (8 kHz). This is enough for human speech to be comprehensible.

44100 Hz

The 44.1 kHz sample rate is used for compact disc (CD) audio. CDs provide uncompressed 16-bit stereo sound at 44.1 kHz. Computer audio also frequently uses this frequency by default.

48000 Hz

The audio on DVD is recorded at 48 kHz. This is also often used for computer audio.

96000 Hz

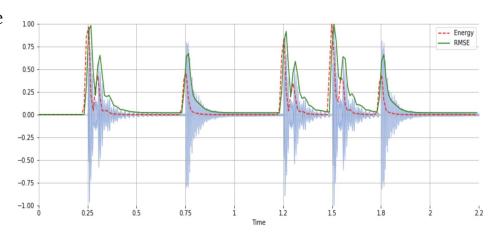
High-resolution audio.

192000 Hz

Ultra-high resolution audio. Not commonly used yet, but this will change over time.

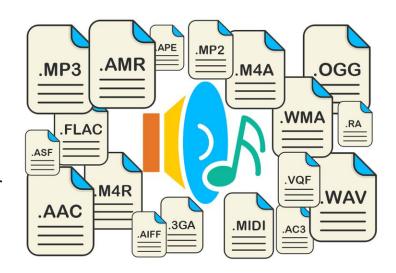
What other characteristics are there?

- Assume **f(n)** is our signal where **n** is time
- Power of signal is $f^2(n)$
- Energy of signal (**E**) is $\sum f^2(n)$
- In practice estimated by some window
- ullet Energy in **decibels**: $10\log_{10}E$
- $ullet ext{SNR}_{dB} = 10 \log_{10} rac{E_{ ext{signal}}}{E_{ ext{noise}}}$



What about audio formats?

- Non-compressed formats: **WAV**, **AIFF**, **etc**.
- Lossless compression(2:1): **FLAC**, **ALAC**, **etc**.
- Lossy compression(10:1): **MP3, Opus, etc**
- Bit rate measure a degree of compression. Number of bit that are conveyed or processed per unit of time.

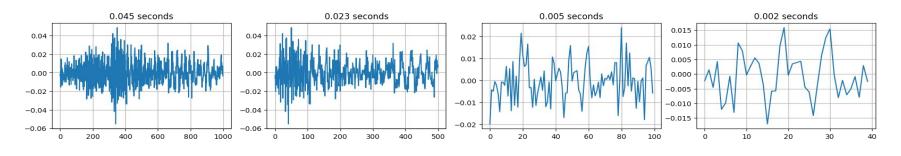


Frequencies and **Spectrograms**

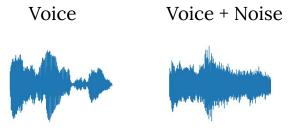
Why not just use wave representation for ML?

Problems with the waveform

• One letter/sound consists of 2000-4000 amplitudes, so they are expensive to process and store



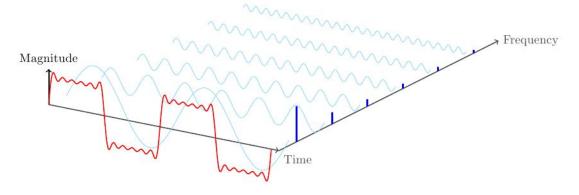
- No "invariant" regarding noise and transformations
- Periodical nature of audio signals

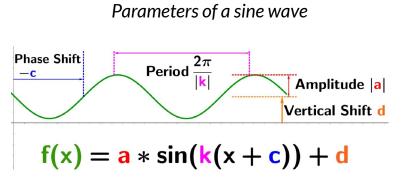


Complex waves as a sum of sigmoids

We want to represent a periodic function as a sum of sigmoids with different periods (frequencies), shifts and amplitudes.

$$f(x) = A_1 * sin(freq_1x + \phi_1) + ...$$
...
...
 $A_n * sin(freq_nx + \phi_n)$





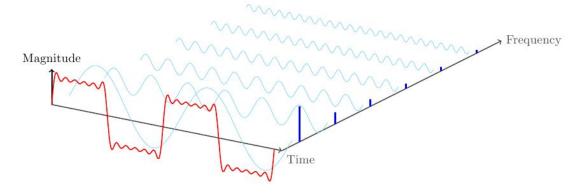
Complex waves as a sum of sigmoids

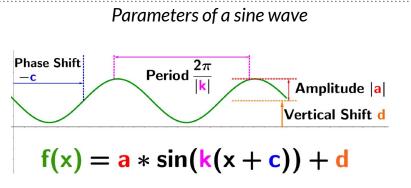
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 $A_n * sin(freq_nx + \phi_n)$

And for audio processing we are only interested in:

- Frequencies
- Amplitudes





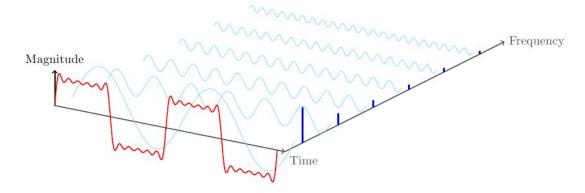
Complex waves as a sum of sigmoids

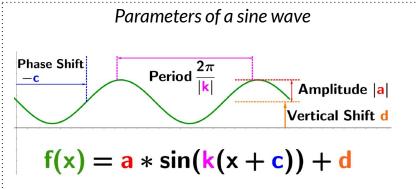
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And for audio processing we are only interested in:

- Frequencies
- Amplitudes
- Phases(?)



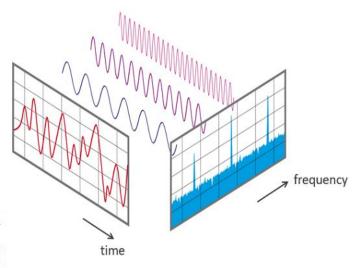


Fourier Transform

- The **Fourier transform(FT)** is a mathematical formula that allows us to decompose a signal into its individual **frequencies** and the frequency's amplitude
- FT transfer a signal from real-valued function of the time domain to a complex-valued function of frequency domain

Fourier transform integral
$$f: \mathbb{R} o \mathbb{R}$$
 $\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x) \ e^{-i2\pi\xi x} \ dx, \quad orall \ \xi \in \mathbb{R}.$ $\hat{f}: \mathbb{R} o \mathbb{C}$

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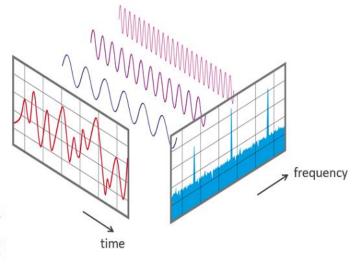
- The function must meet the following conditions:
 - to be **bounded**
 - to be absolutely integrable
 - to have a **finite number** of minimas, maximas and discontinuities

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Original signal Frequency



Inverse Fourier Transform

Fourier transform integral

$$\left|\hat{f}\left(\xi
ight)=\int_{-\infty}^{\infty}f(x)\;e^{-i2\pi\xi x}\,dx,\quadorall\;\xi\in\mathbb{R}.
ight|$$

Fourier inversion integral

$$f(x)=\int_{-\infty}^{\infty}\hat{f}\left(\xi
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Inverse Fourier Transform

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$$f(x)=\int_{-\infty}^{\infty}\hat{f}\left(\xi
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$$=2\int_{0}^{\infty}\operatorname{Re}\Bigl(\hat{f}\left(\xi
ight)\cdot e^{i2\pi\xi x}\Bigr)d\xi$$

Property of FT

$$\hat{f}\left(\xi
ight) = \left\{ egin{array}{ll} \displaystyle \int_{-\infty}^{\infty} f(x) \; e^{-i2\pi \xi x} \; dx, \qquad & \xi \geq 0 \ \displaystyle \hat{f}^{st}(|\xi|) & & \xi < 0, \end{array}
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Inverse Fourier Transform

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Fourier transform integral

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Euler's formula

$$e^{jx} = \cos x + j\sin x$$

Fourier inversion integral

$$f(x)=\int_{-\infty}^{\infty}\hat{f}\left(\xi
ight)e^{i2\pi\xi x}\,d\xi,\quadorall\ x\in\mathbb{R},$$

$$egin{aligned} &=2\int_{0}^{\infty}\mathrm{Re}\Big(\hat{f}\left(\xi
ight)\cdot e^{i2\pi\xi x}\Big)d\xi \ &=2\int_{0}^{\infty}\left(\mathrm{Re}(\hat{f}\left(\xi
ight))\cdot\cos(2\pi\xi x)-\mathrm{Im}(\hat{f}\left(\xi
ight))\cdot\sin(2\pi\xi x)
ight)d\xi. \end{aligned}$$

Discrete Fourier Transform (DFT)

How to calculate Fourier Transform in practice?

- Operates on signal X consisting of N uniformly sampled across [0,T] points
- Discrete analogue of FT: at frequency number k (which is 2πk/N*sampleRate Hz) it gives a complex number

$$\hat{X}_k = \sum_{t=0}^{N-1} X_t e^{-\frac{2\pi ki}{N}t}$$

- Operates on signal X consisting of N uniformly sampled across [0,T] points
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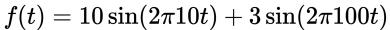
$$\hat{X}_{k} = a_{k}e^{-i\phi_{k}} = a_{k}(cos(\phi_{k}) - isin(\phi_{k}))$$
 frequency amplitude

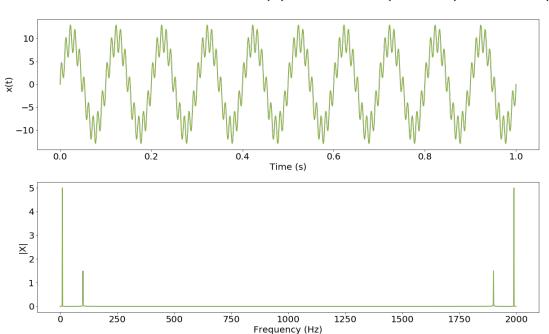
$$\hat{X} = MX$$

$$M_{mn} = \exp\left(-2\pi i \frac{(m-1)(n-1)}{N}\right)$$

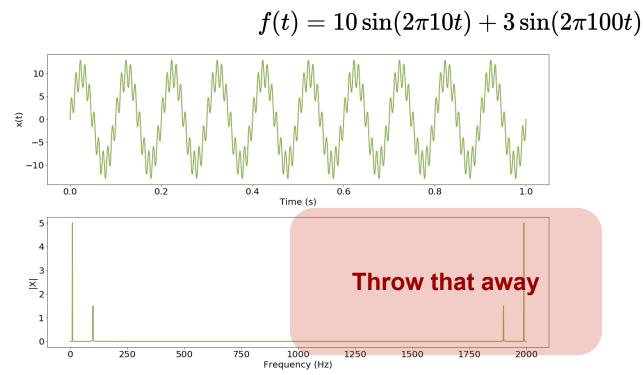
$$\mathbf{M} = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & e^{-\frac{2\pi i}{N}} & e^{-\frac{4\pi i}{N}} & e^{-\frac{6\pi i}{N}} & \dots & e^{-\frac{2\pi i}{N}(N-1)} \\ 1 & e^{-\frac{4\pi i}{N}} & e^{-\frac{8\pi i}{N}} & e^{-\frac{12\pi i}{N}} & \dots & e^{-\frac{2\pi i}{N}2(N-1)} \\ 1 & e^{-\frac{6\pi i}{N}} & e^{-\frac{12\pi i}{N}} & e^{-\frac{18\pi i}{N}} & \dots & e^{-\frac{2\pi i}{N}3(N-1)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & e^{-\frac{2\pi i}{N}(N-1)} & e^{-\frac{2\pi i}{N}2(N-1)} & e^{-\frac{2\pi i}{N}3(N-1)} & \dots & e^{-\frac{2\pi i}{N}(N-1)^2} \end{pmatrix}$$

Example of DFT



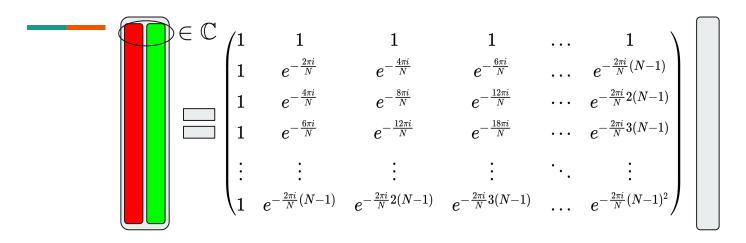


Example of DFT



Why spectrum is mirroring?

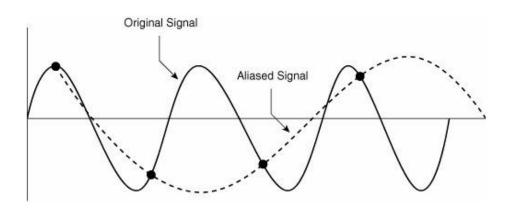
$$egin{align} X_m &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pirac{m}{N}n
ight) \ X_{N-m} &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pirac{N-m}{N}n
ight) \ &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pi n + j2\pirac{m}{N}n
ight) \ &= \sum_{n=0}^{N-1} x_n \exp\left(j2\pirac{m}{N}n
ight) \ &= (X_m)^* \end{aligned}$$



$$\hat{X}_{k} = a_{k}e^{-i\phi_{k}} = a_{k}(cos(\phi_{k}) - isin(\phi_{k}))$$
 frequency amplitude

Kotelnikov Theorem

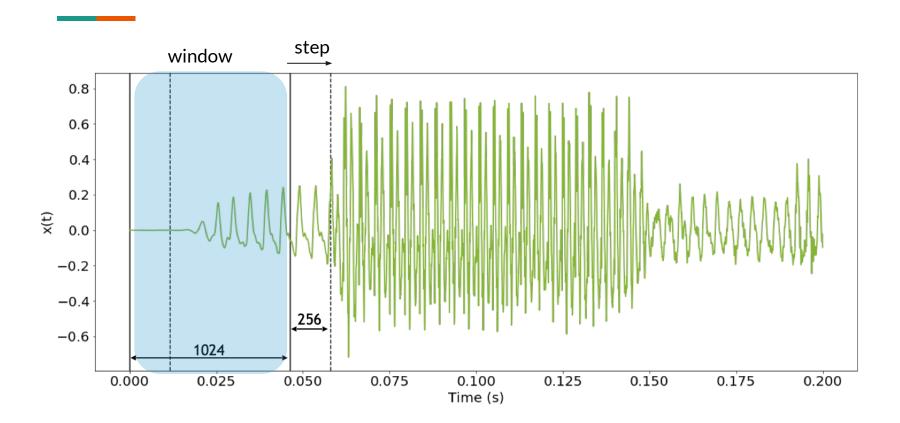
- If a function **f(t)** contain no frequencies higher than **B hertz**, it is completely determined by giving its ordinates at series of points spaced **1/2B** seconds apart
- **Example:** If signal contains frequency 100 Hz, the sampling rate for this signal needs to be 200 Hz at least
- DFT of a segment of a signal with sample rate N, will produce amplitudes for nfft evenly spread frequencies in range [-sampleRate / 2; sampleRate / 2]



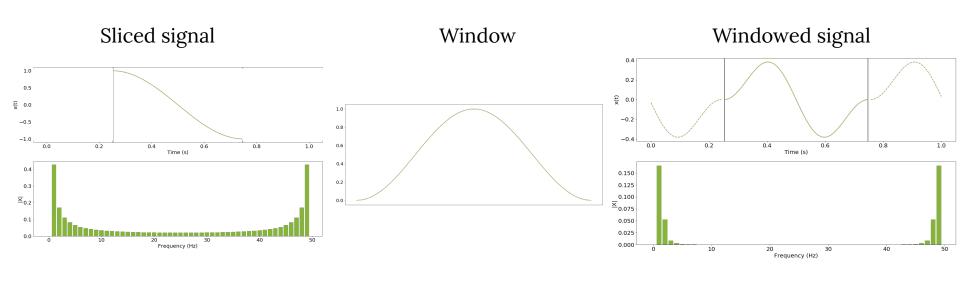
Short Time Fourier Transform (STFT)

How to apply FT to a long non-periodic signal?

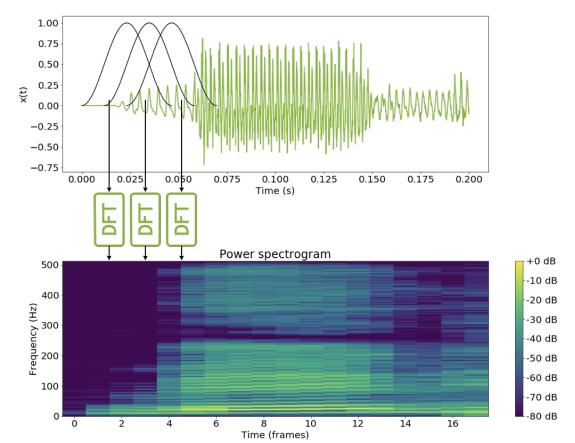
Short-Time Fourier Transform



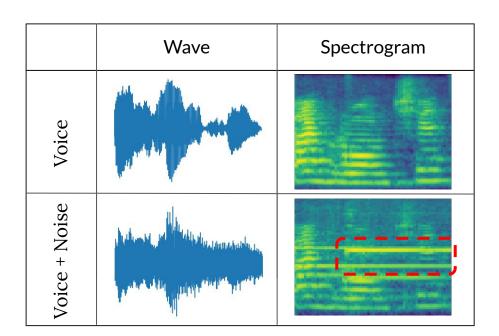
Window functions



Short Time Fourier Transform + window function



Spectrogram



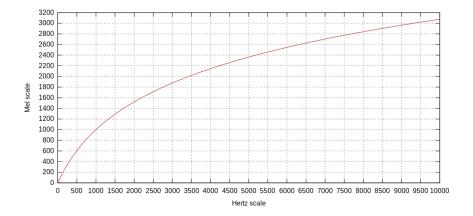
Practical use: values of the spectrogram are very small, so typically the log-spectrogram is used instead

Mel Scale

Compressing the spectrogram

Mel Scale

- Humans perceive sound on a log-scale. For human ear:
 - 500 Hz << 600 Hz
 - but 5000 Hz ~= 5100 Hz



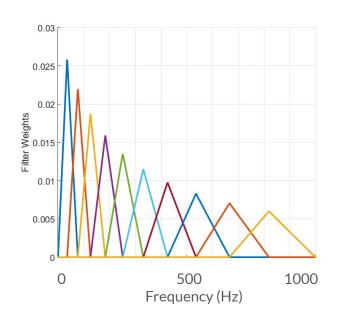
There is no single mel-scale formula. [3] The popular formula from O'Shaughnessy's book can be expressed with different logarithmic bases:

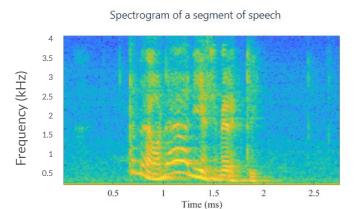
$$m = 2595 \log_{10} \left(1 + rac{f}{700}
ight) = 1127 \ln \left(1 + rac{f}{700}
ight)$$

The corresponding inverse expressions are:

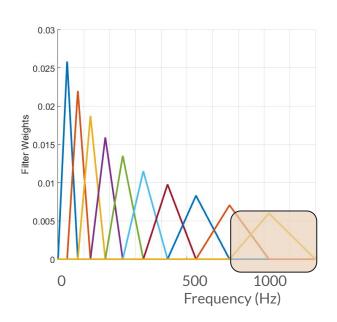
$$f = 700 \left(10^{rac{m}{2595}} - 1
ight) = 700 \left(e^{rac{m}{1127}} - 1
ight)$$

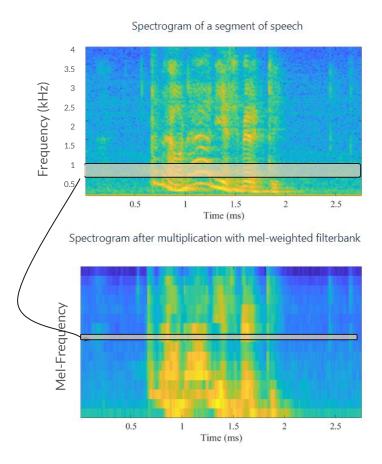
Mel Spectrogram





Mel Spectrogram





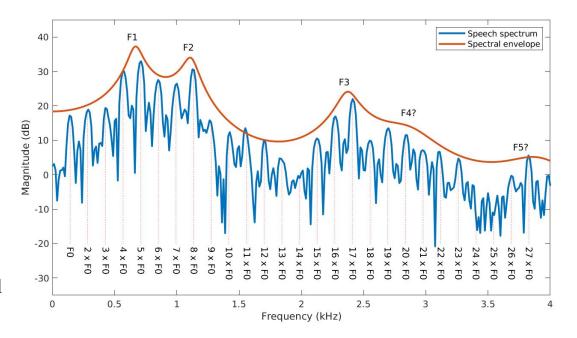
MFCC

Decorrelating the spectrogram

- Sound representation
- Motivation for spectrograms
- Fourier Transform
- Discrete Fourier Transform
- Short Time Fourier Transform
- Spectrogram
- Mel scale
- MFCC

Fundamental Frequency

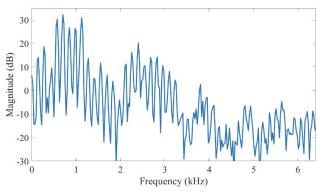
- Fundamental frequency
 refers to the approximate
 frequency of the
 (quasi-)periodic structure of
 voiced speech signals
- Peaks on envelope curve are **formants**
- **Pitch** is perceptual value, F0 is physical
- F0 lie roughly in the range 80 to 450 Hz, where males have lower voices than females and children



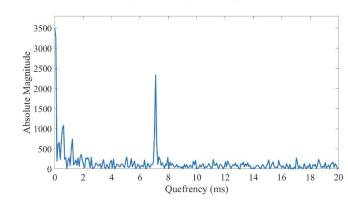
Cepstrum

- Fourier spectrum of voice has **periodic** structure
- Apply DCT (Discrete Cosine Transform) to spectrum and obtain Cepstrum
- **Peak** in Cepstrum should be located at \overline{I}





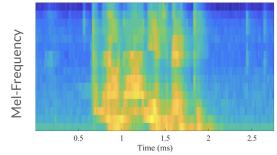
Cepstrum of speech segment



Mel-Frequency Cepstral Coefficients (MFCCs)

- Algorithm of acquiring MFCC:
 - Apply STFT to the signal
 - Apply mel filters
 - o Take the log value
 - Apply DCT

Spectrogram after multiplication with mel-weighted filterbank



Corresponding MFCCs

