

Digital Signal Processing 1

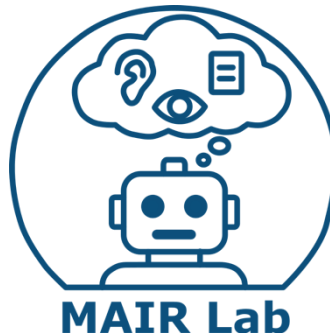
안인규 (Inkyu An)

Speech And Audio Recognition
(오디오 음성인식)

<https://mairlab-km.github.io/>

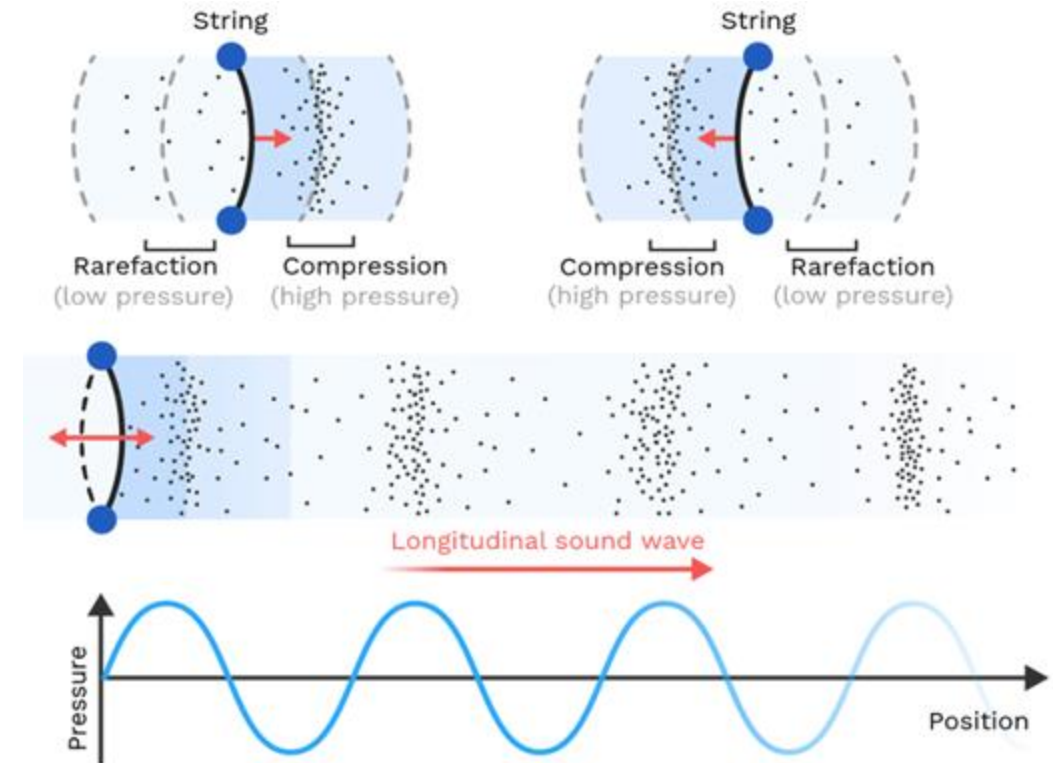


This lecture material refers to
https://github.com/yandexdataschool/speech_course?tab=readme-ov-file and
<https://github.com/markovka17/dla>



What is Sound?

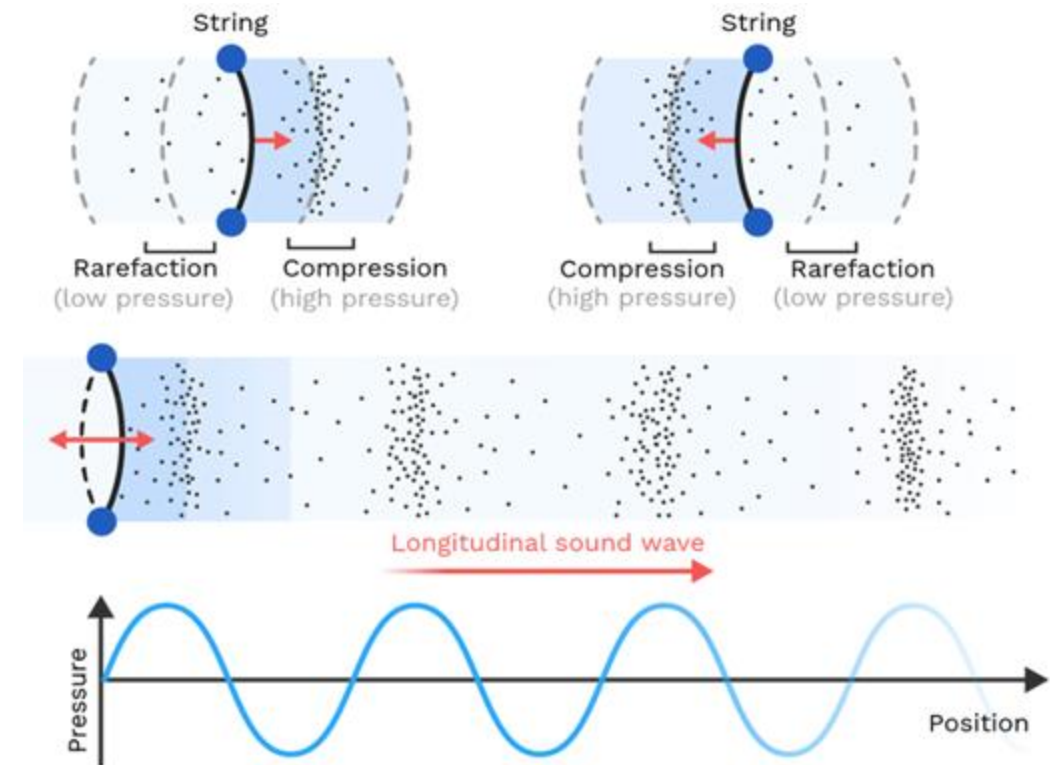
- The air around us is filled with molecules.
- When you pull a guitar string, it creates a vibration that moves through the molecules in the air.
- The regions of high pressure are compressions and the regions of low pressure as rarefactions.



What is Sound?

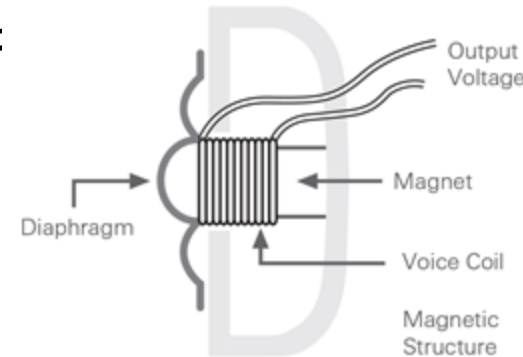
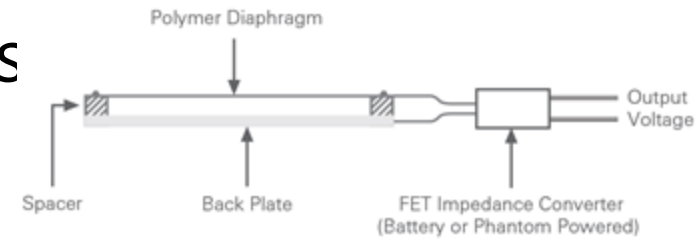
The microphone detects these variations in pressure.

When we plot pressure, **relative to atmospheric** pressure, against the position near the string, we see the familiar sinusoidal waveform.

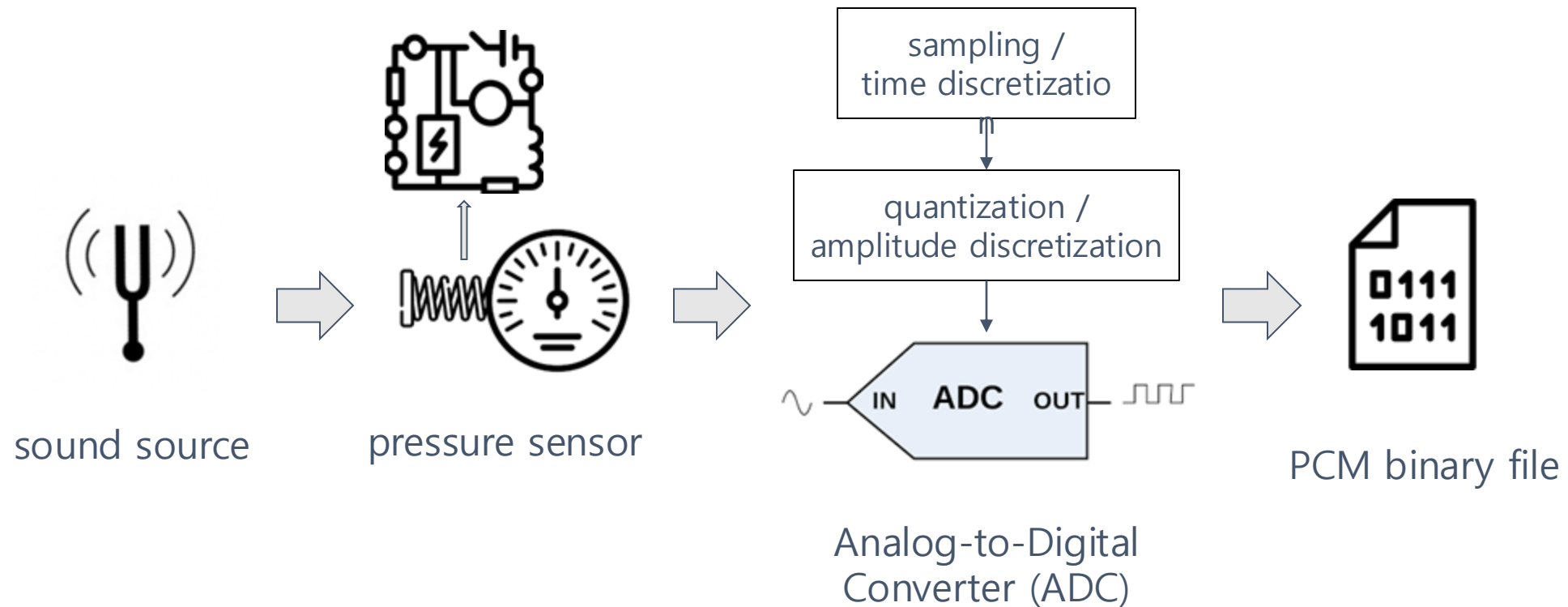


Recording

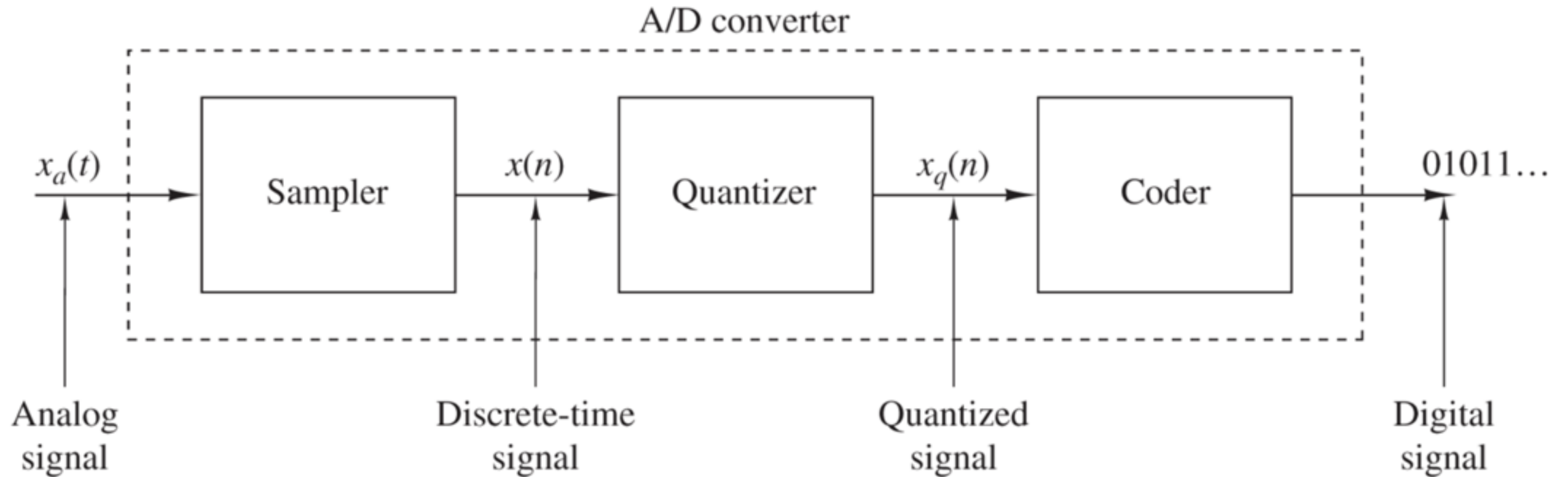
- To record people use microphones
- Microphone picks up these air oscillations in continuous form
- These oscillations are converted into an analog signal and then a digital signal



Analog and Digital Signals

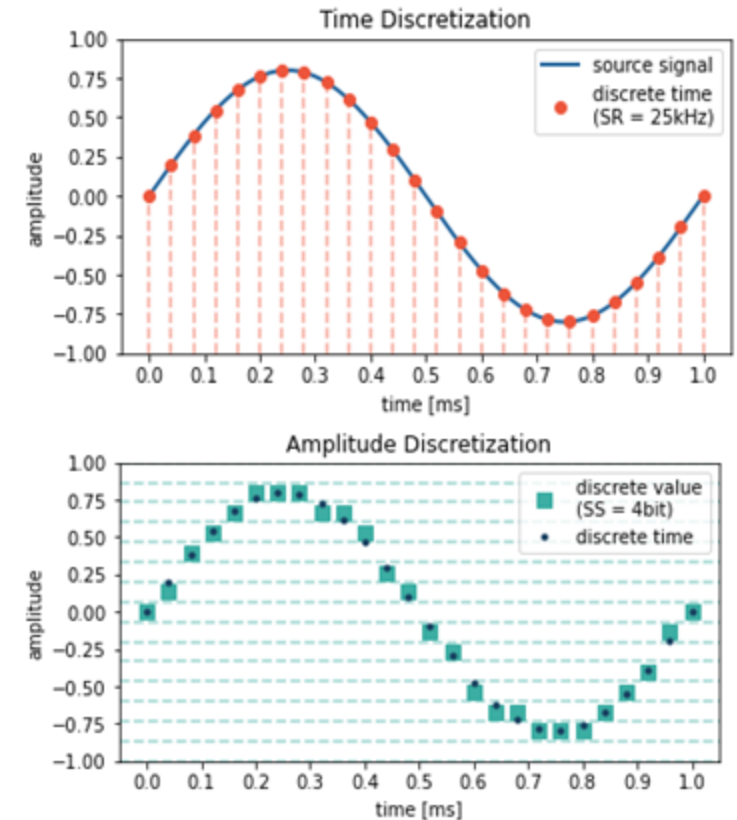


Analog and Digital Signals



Waveform as Pulse-Code Modulation (PCM)

- **Time discretization:** we represent the analog signal as a sequence of samples measured at discrete points in time
 - **Sample rate** – number of audio samples per second (8kHz, 22.05kHz, 44.1kHz)
- **Amplitude discretization:** round continuous amplitude to the nearest discrete value
 - **Bit depth** – number of bits per sample (eg. 8, 16, 24, 32 bits)
 - **Bit rate** = bit-depth * sample-rate * audio-channels
- **Number of channels:** number of signals recorded in parallel (e.g., mono vs. stereo)



Properties of Waveforms: Intensity

Intensity is defined to be the *energy* (E) per unit *area* (A) and time unit (t) carried by a wave:

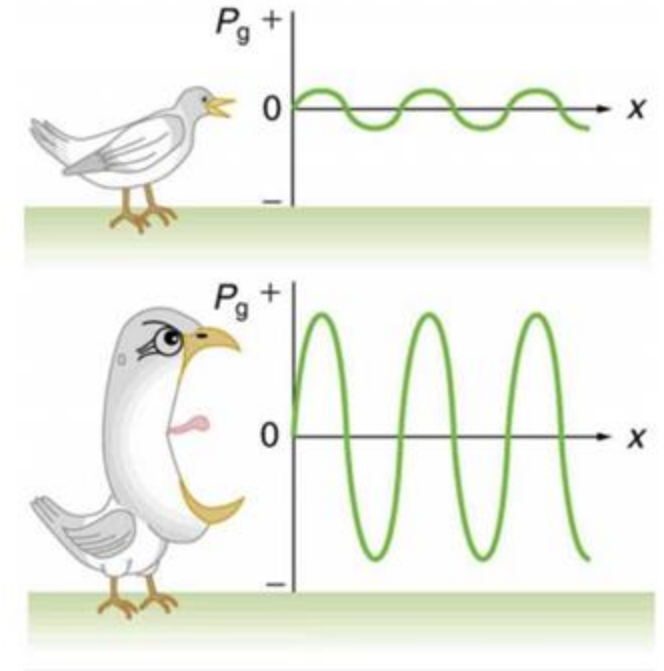
$$I = \frac{E}{tA} = \frac{P}{A} \quad \leftarrow \text{power}$$

The intensity of a sound wave is proportional to its amplitude squared:

$$I \sim (\Delta p)^2$$

For a discrete-time signal $\{p_n\}_{1:T}$ of length T :

$$I_n \sim p_n^2$$



Properties of Waveforms: Loudness

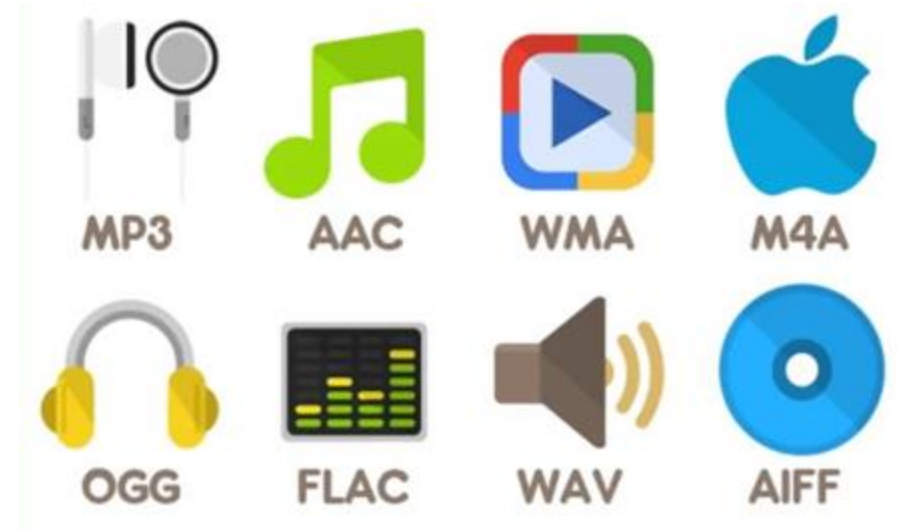
- **Loudness** is intensity measured in decibel
- **bel** reports \log_{10} of ratio between measuring signal and reference signal
- In physics, **decibels** are used instead of bels because 1 bel is too large

$$I_{dB} = 10 \log \left(\frac{I}{I_0} \right) = 10 \log \left(\frac{p^2}{p_0^2} \right) = 20 \log \left(\frac{p}{p_0} \right)$$



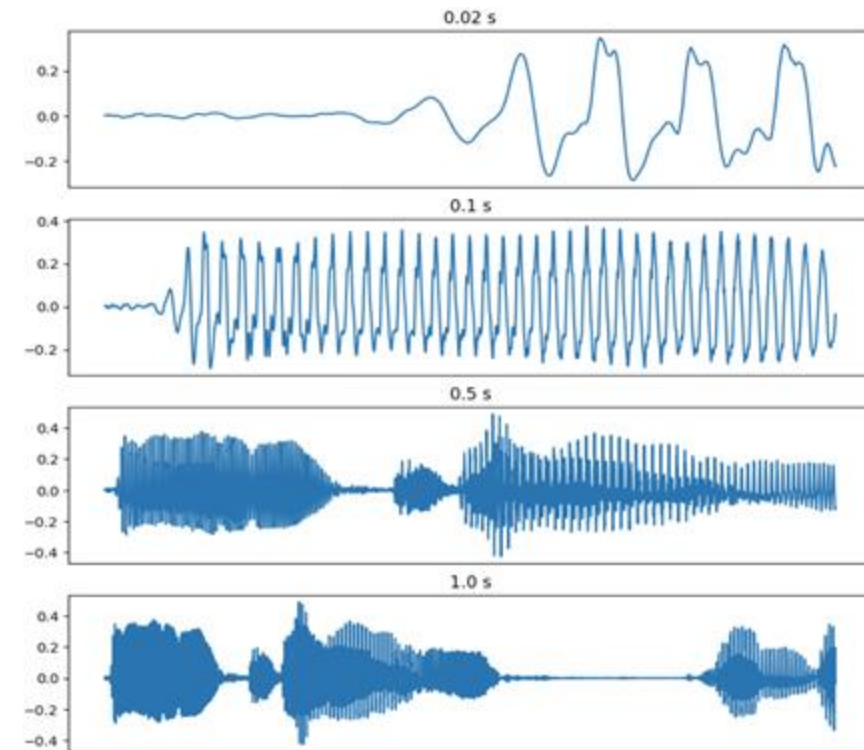
What about audio formats?

- Uncompressed: WAV, AIFF
- Lossless compression: FLAC, ALAC
- Lossy compression: MP3, Opus



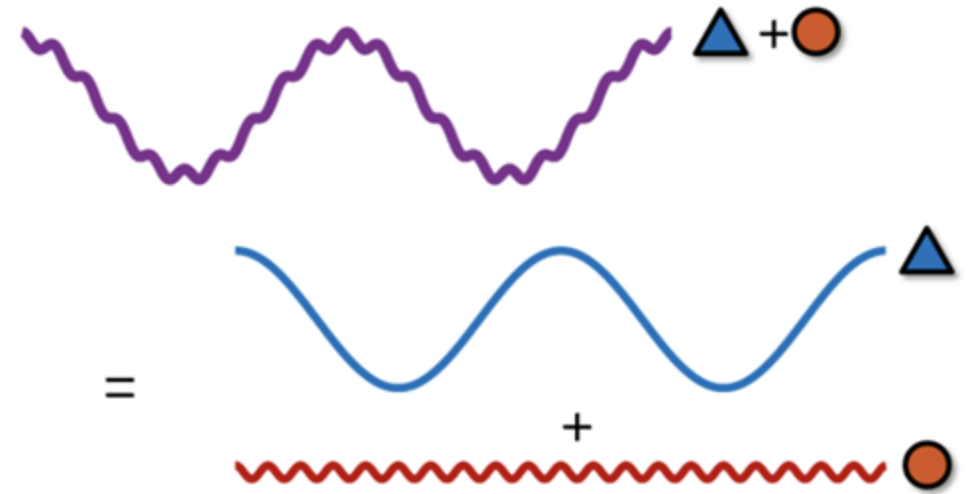
Difficulties in using waveforms

- Waveform is really long (e.g. 44K samples / sec)
- Waveforms provide limited insight into a recording's pitch and speech content
- Can we get a more compact and informative sound representation?



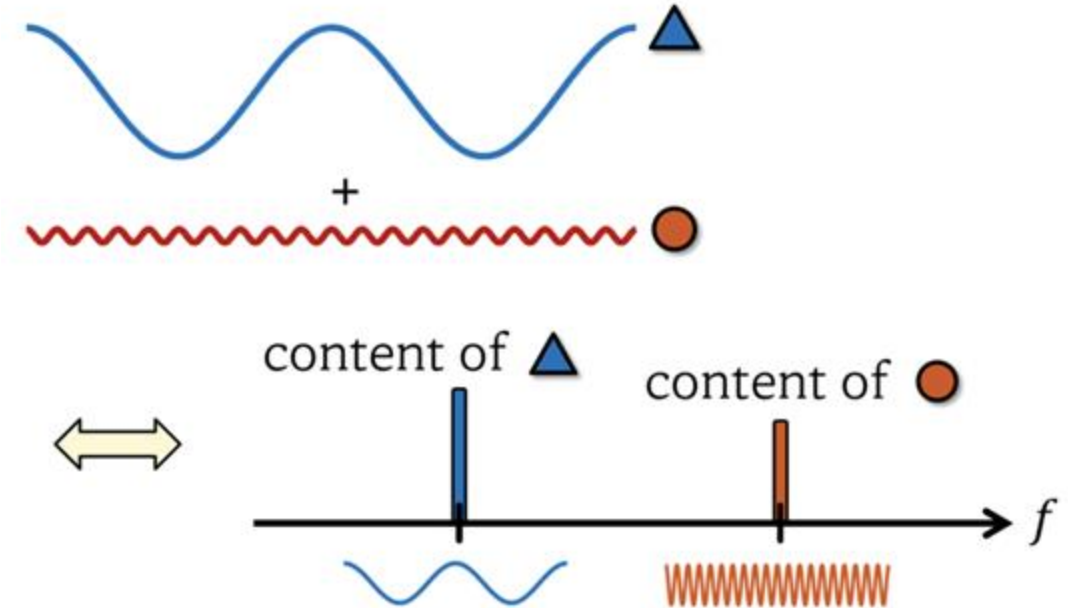
Fourier Analysis

- At its core, Fourier analysis breaks down complex signals into their frequency components.
- It's similar to breaking down a song into its individual musical notes.



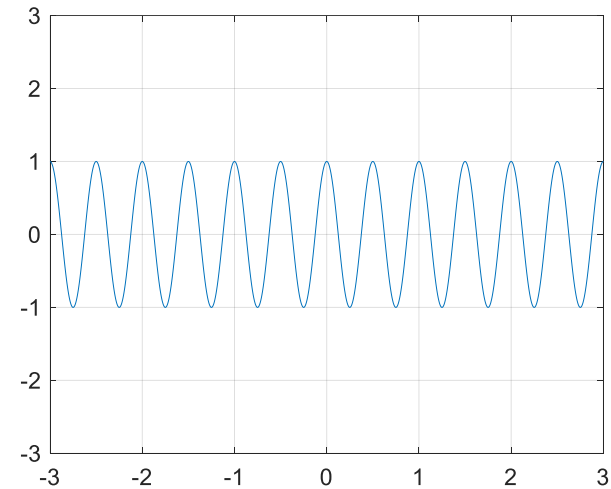
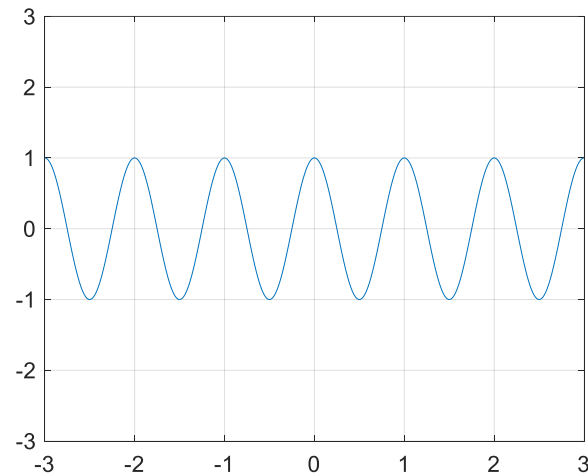
Fourier Analysis

- The amplitudes of these frequency components appear on the frequency axis rather than the time axis, forming what's called the (frequency) spectrum



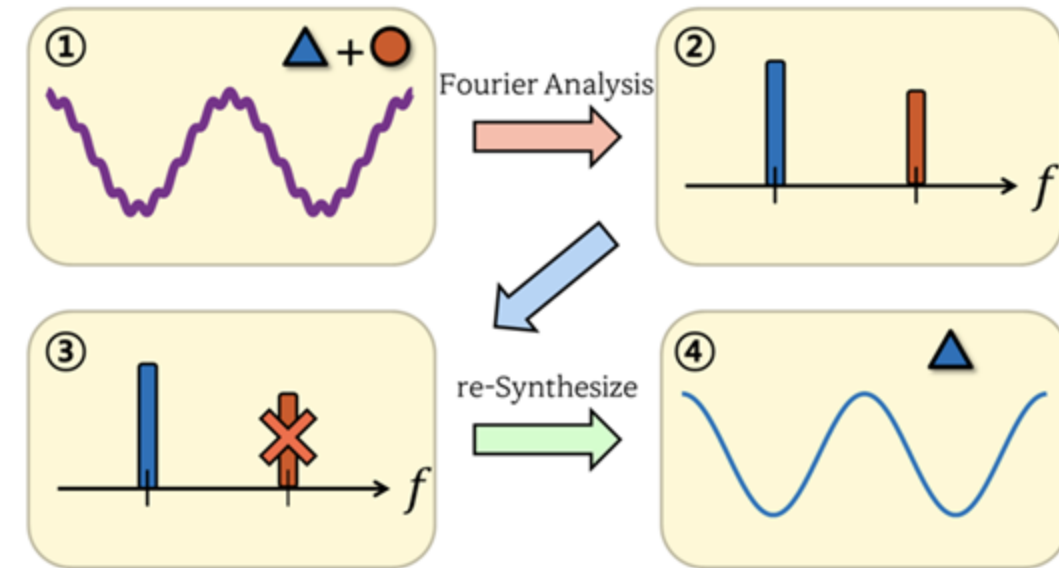
Fourier Analysis

- What is Frequency?
 - Period: T
 - Frequency: $f=1/T$
- Question:
 - What is the frequency of the below graph?



Fourier Analysis

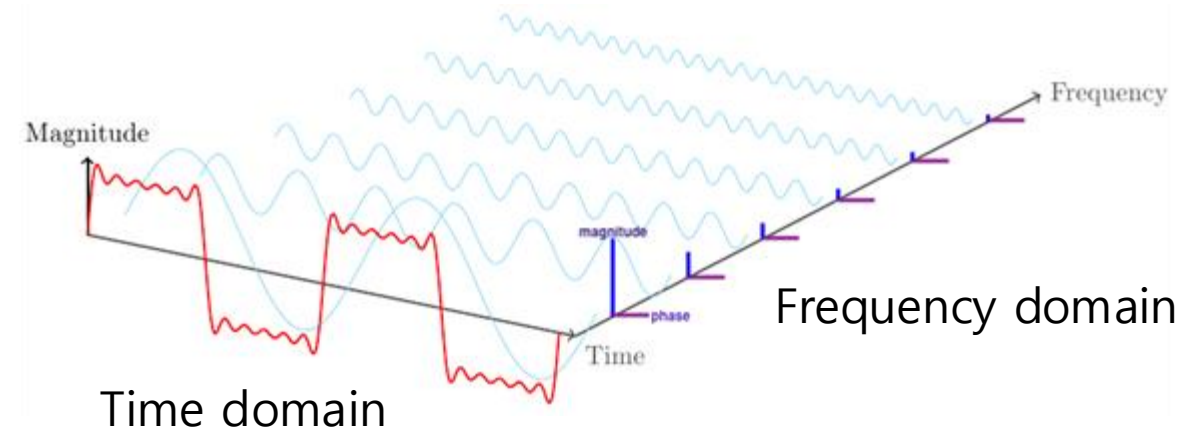
- The usefulness of Fourier analysis:
 - It converts a long sequence of time samples into a compact frequency representation.
 - It enables analysis of frequency components and filtering of unwanted frequencies.



Fourier Series

- Any absolutely integrable periodic function $x(t)$ with period P can be represented as

$$x(t) = \frac{A_0}{2} + \sum_{n=1}^{\infty} A_n \cos\left(2\pi \frac{n}{P} t - \phi_n\right)$$

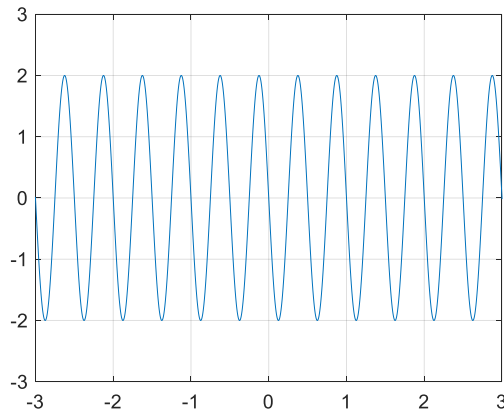


Fourier Series

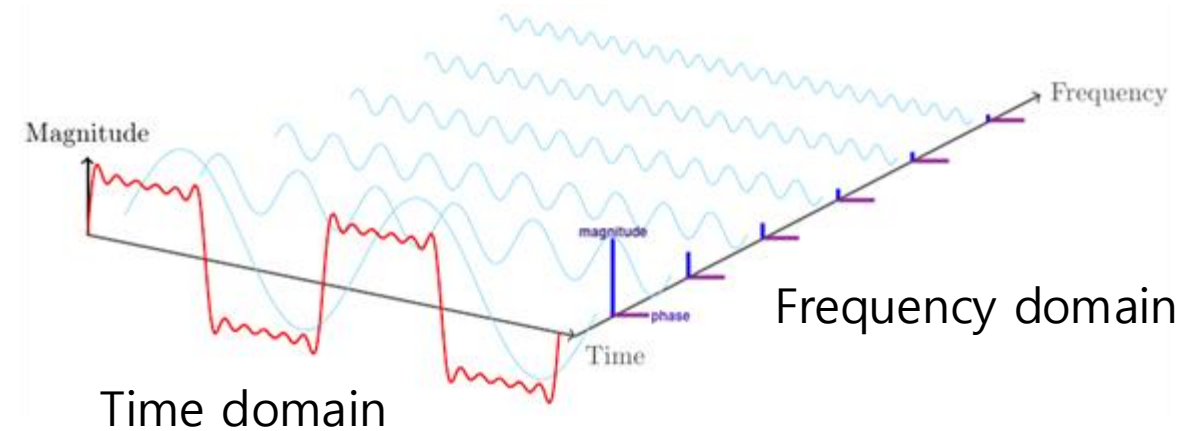
- Any absolutely integrable periodic function $x(t)$ with period P can be represented as

$$x(t) = \frac{A_0}{2} + \sum_{n=1}^{\infty} \underbrace{A_n}_{\text{Amplitude}} \cos\left(2\pi \underbrace{\frac{n}{P}}_{\text{Frequency}} t - \underbrace{\phi_n}_{\text{Phase}}\right)$$

- What is the amplitude and the phase?



- Amplitude?
- Phase?



Fourier Series

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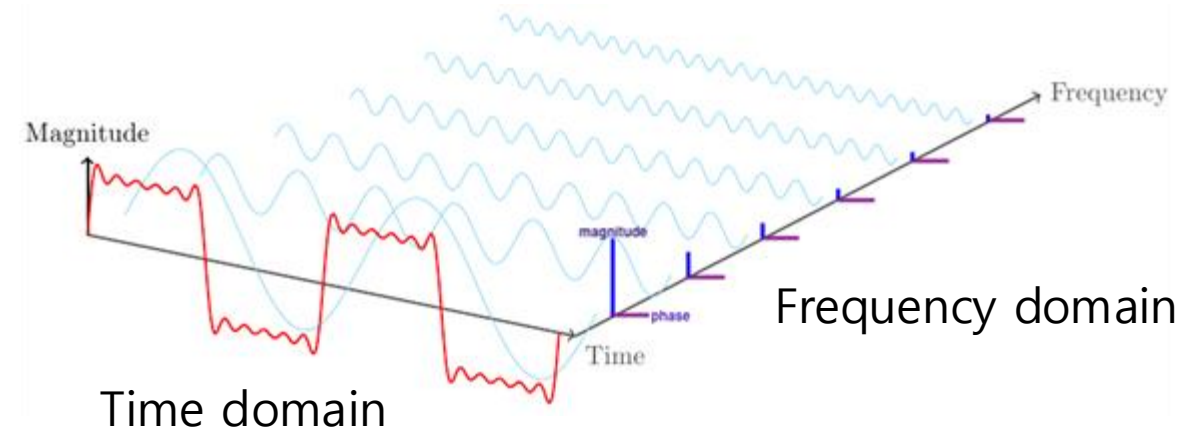
Fourier Series: Amplitude-phase form

$$= a_0 + \sum_{n=1}^{\infty} \left(a_n \cos\left(\frac{2\pi n t}{P}\right) + b_n \sin\left(\frac{2\pi n t}{P}\right) \right)$$

Fourier Series: sine-cosine form

$$= \sum_{n=-\infty}^{\infty} c_n e^{2\pi i \frac{n}{P} t}$$

Fourier Series: exponential form



Fourier Series

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Fourier Series: sine-cosine form

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Fourier Series: exponential form

Use formular for cosine of the difference
 $\cos(A - B) = \cos A \cos B + \sin A \sin B$

Use Euler's formula

$$\cos x = \frac{e^{ix} + e^{-ix}}{2}$$

$$\sin x = \frac{e^{ix} - e^{-ix}}{2i}$$

Fourier Series

Exponential form coefficients

$$c_n = \begin{cases} \frac{1}{2}(a_n - ib_n) & \text{if } n > 0, \\ a_n & \text{if } n = 0, \\ \frac{1}{2}(a_{-n} + ib_{-n}) & \text{if } n < 0, \end{cases}$$

- Any absolutely integrable periodic function $x(t)$ with period P can be represented as

$$x(t) = \frac{A_0}{2} + \sum_{n=1}^{\infty} A_n \cos\left(2\pi \frac{n}{P} t - \phi_n\right)$$

Fourier Series: Amplitude-phase form

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Fourier Series: exponential form

Use Euler's formula

$$\cos x = \frac{e^{ix} + e^{-ix}}{2}, \quad \sin x = \frac{e^{ix} - e^{-ix}}{2i}$$

Fourier Series: Exponential form

- Fourier Series & Fourier Coefficient

$$x(t) = \sum_{n=-\infty}^{\infty} c_n e^{2\pi i \frac{n}{P} t}$$

$$c_n = \frac{1}{P} \int_0^P x(t) e^{-2\pi i \frac{n}{P} t} dt$$

Fourier coefficient

- The set of Fourier coefficients is also called the **spectrum** of $x(t)$
- c_n are **complex** numbers

Fourier Transform

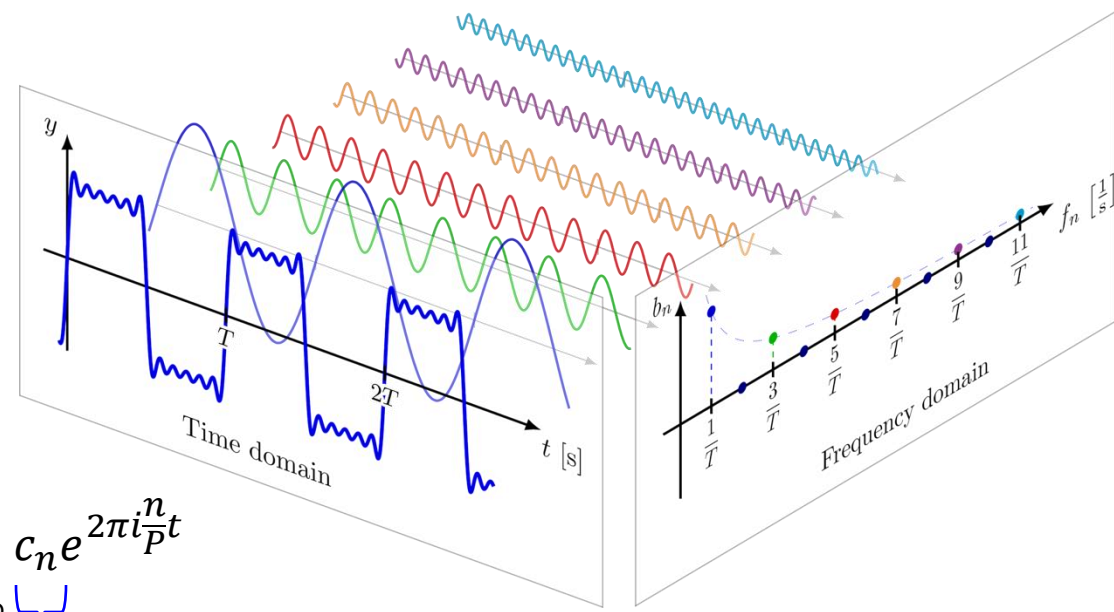
- Fourier Series & Fourier Coefficient

P : the period

$$c_n = \frac{1}{P} \int_0^P x(t) e^{-2\pi i \frac{n}{P} t} dt$$

Fourier coefficient

$$x(t) = \sum_{n=-\infty}^{\infty} c_n e^{2\pi i \frac{n}{P} t}$$



- Let's assume $P \rightarrow \infty$ and $0 \rightarrow -\infty$



$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-2\pi i f t} dt$$

Frequency

Original signal

Fourier transform

- Fourier Transform!

- A mathematical formula that allows us to decompose any signal into its individual **frequencies** and the frequency's **amplitude**

Fourier Transform



- Fourier Transform!
 - A mathematical formular that allows us to decompose any signal into its individual **frequencies** and the frequency's **amplitude**

Frequency

Original signal

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-2\pi i f t} dt$$

Fourier transform

- There is also the inverse Fourier Transform:

Original signal

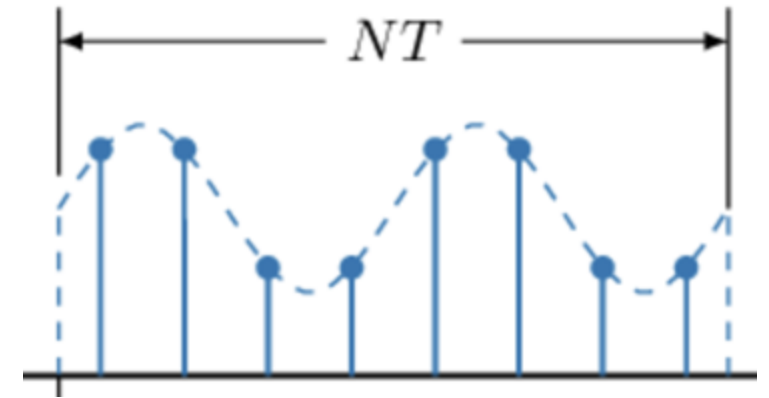
Frequency

$$x(t) = \int_{-\infty}^{\infty} X(f) e^{2\pi i f t} dt$$

Inverse Fourier transform

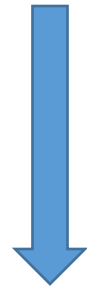
Discrete-Time Fourier Series (DTFS)

- In practice our time signal is time-limited and contains N non-zero samples taken with a sampling period T seconds.
- Let's explore what happens when we try to find its Fourier coefficients.



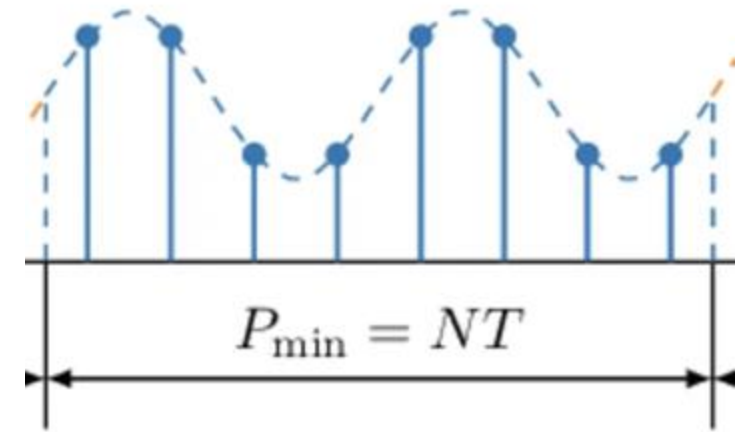
Discrete-Time Fourier Series (DTFS)

$$c_k = \frac{1}{P} \int_0^P x(t) e^{-2\pi i \frac{n}{P} t} dt$$



- The integral "turns" into a sum over a discrete set of values
- $P = NT$

$$X[k] = \frac{1}{NT} \sum_{n=0}^{N-1} x(nT) e^{-2\pi i \frac{k}{NT} nT}$$



Discrete-Time Fourier Series (DTFS)

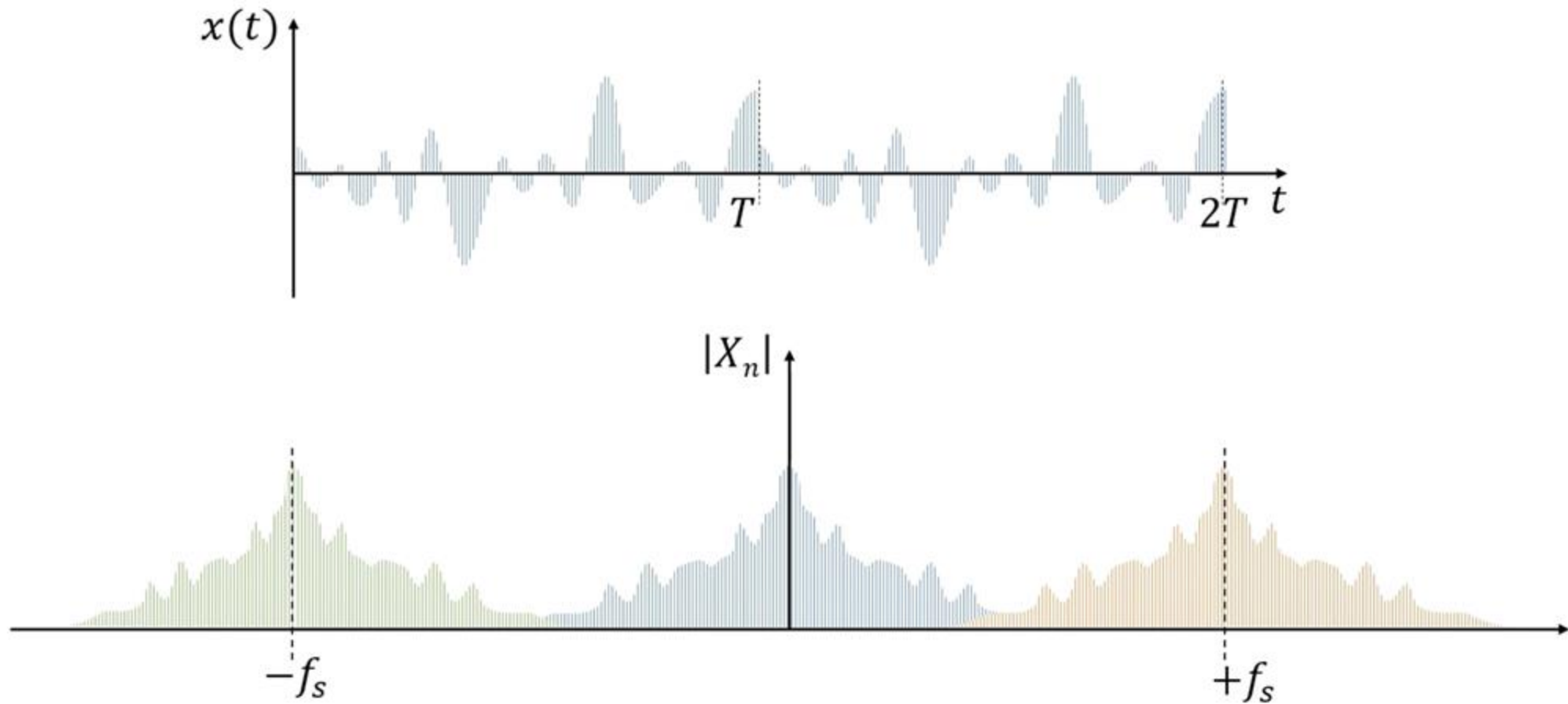
- Disappears! Now the basis functions are defined by N :

$$c_k = \frac{1}{NT} \sum_{n=0}^{N-1} x(nT) e^{-2\pi i \frac{k}{NT} nT} = \frac{1}{NT} \sum_{n=0}^{N-1} x(nT) e^{-2\pi i \frac{k}{N} n}$$

- The expression above is valid for any integer k but it is *periodic* and repeats every N samples:

$$c_{k+N} = \frac{1}{NT} \sum_{n=0}^{N-1} x(nT) e^{-2\pi i \frac{k+N}{N} n} = \frac{1}{NT} \sum_{n=0}^{N-1} x(nT) e^{-2\pi i \frac{k}{N} n} \cdot \underbrace{e^{-2\pi i n}}_{=1} = c_k$$

Discrete-Time Fourier Series (DTFS)



Discrete Fourier Transform (DFT)

- If we operate only with indices of the input signal and spectral samples (setting $T = 1$), we obtain the Discrete Fourier Transform expression:

$$X[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-2\pi i \frac{k}{N} n}$$

- We can also write out the expression for the Inverse Discrete Fourier Transform (we'll skip the complete derivation):

$$x[n] = \sum_{k=0}^{N-1} X[k] e^{2\pi i \frac{n}{N} k}$$

Digital Signal Processing 2

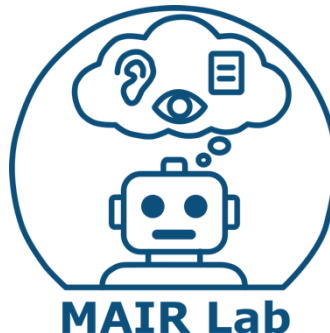
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- We can also write out the expression for the Inverse Discrete Fourier Transform (we'll skip the complete derivation):

$$x[n] = \sum_{k=0}^{N-1} X[k] e^{2\pi i \frac{n}{N} k}$$

$$X[k] = \underset{\text{amplitude}}{a_k} e^{-i \underset{\text{phase}}{\phi_k}} = a_k (\cos(\phi_k) - i \sin(\phi_k))$$

Discrete Fourier Transform (DFT)

- $X = M \cdot x$, where $x = \{x[0], \dots, x[N-1]\}$ and $X = \{X[0], \dots, X[N-1]\}$

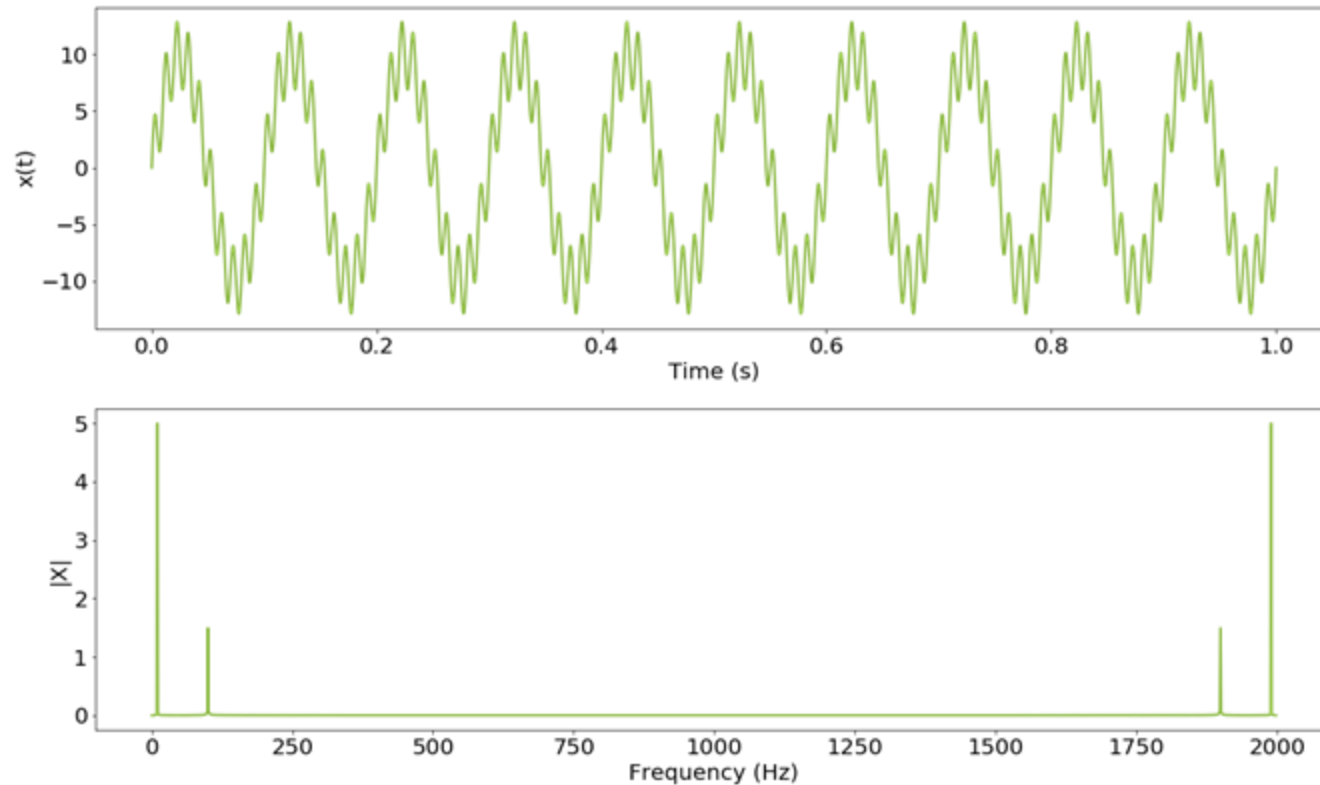
$$M_{mn} = \exp\left(-2\pi i \frac{(m-1)(n-1)}{N}\right)$$

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

We can compute it with FFT, which is extremely fast (theoretically $O(N \log N)$ for signal of size N)

Discrete Fourier Transform (DFT)

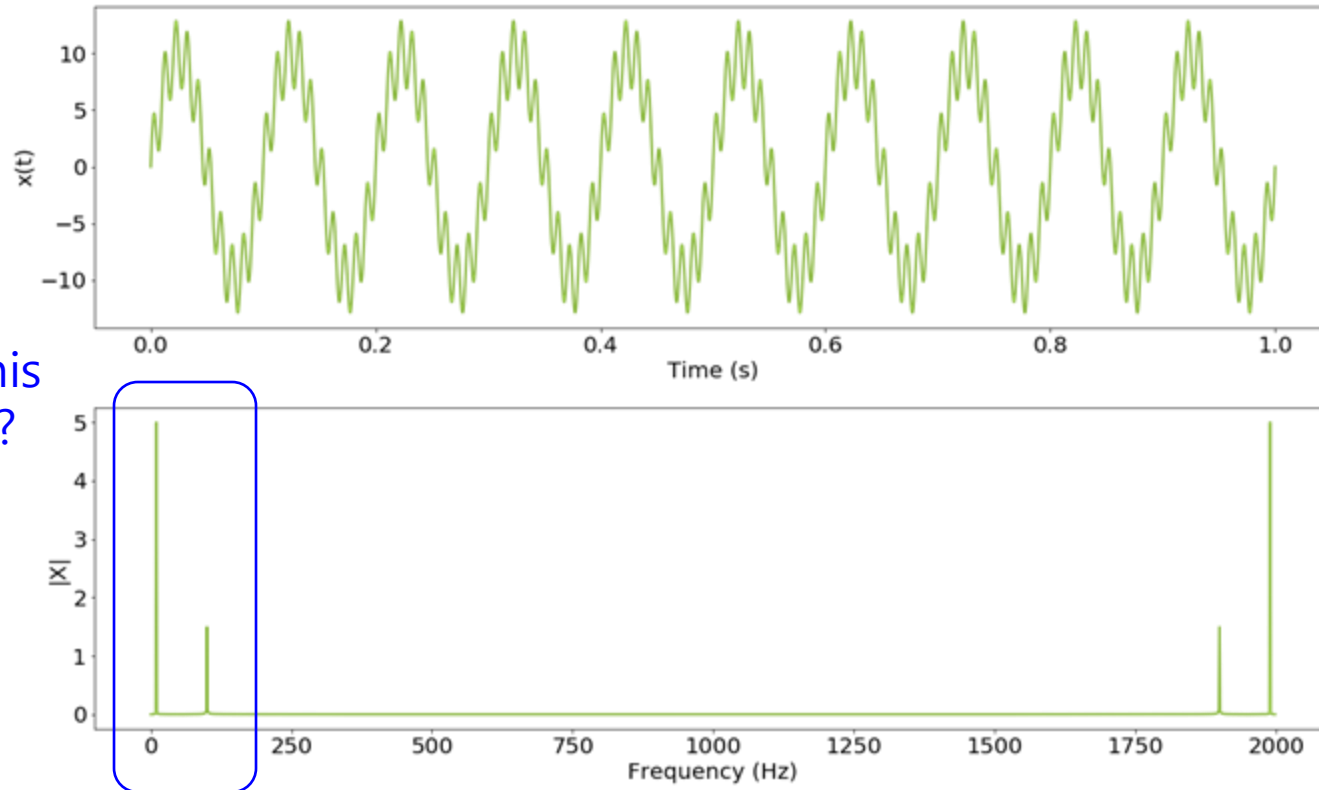
- Example of DFT:
 - $f(t) = 10 \sin(2\pi 10t) + 3 \sin(2\pi 100t)$



Discrete Fourier Transform (DFT)

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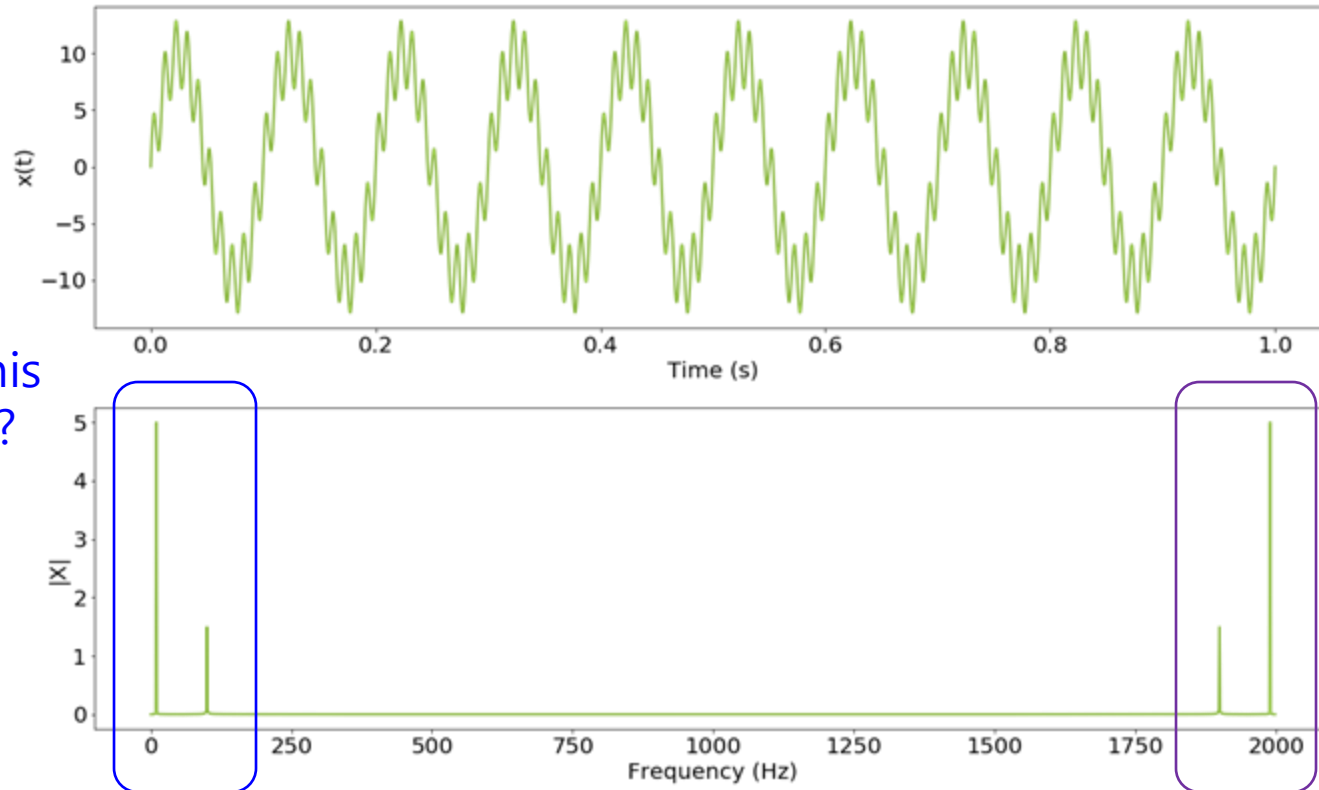
1. What does this graph indicate?



Discrete Fourier Transform (DFT)

- Example of DFT:
 - $f(t) = 10 \sin(2\pi 10t) + 3 \sin(2\pi 100t)$

1. What does this graph indicate?



2. Why does this part keep repeating?

Discrete Fourier Transform (DFT)

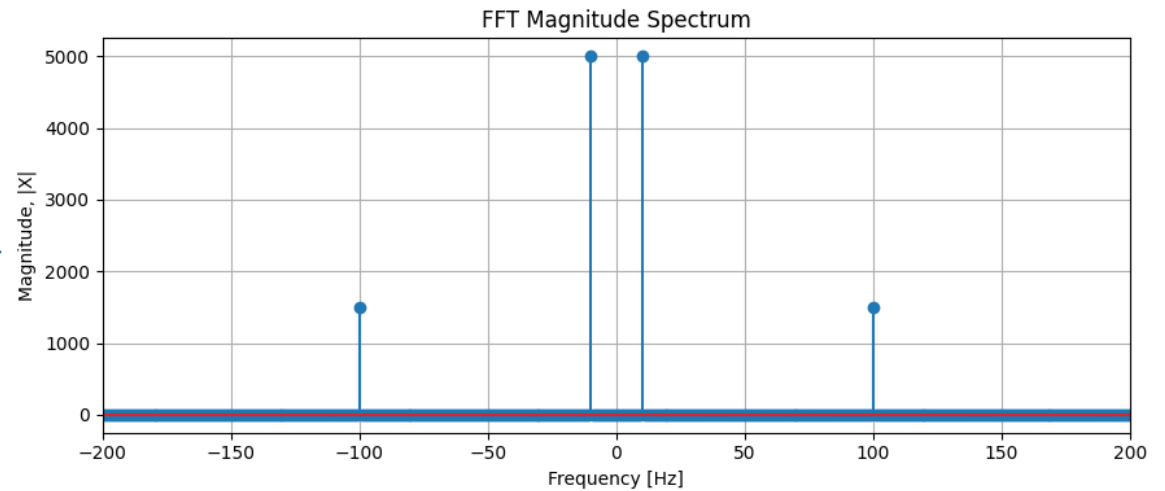
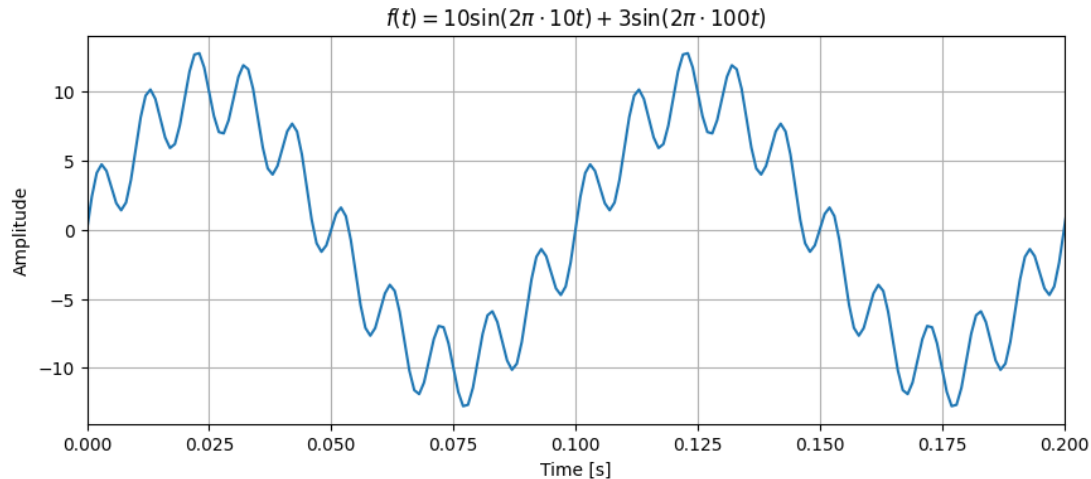
- Example of DFT:
 - $f(t) = 10 \sin(2\pi 10t) + 3 \sin(2\pi 100t)$

$$\begin{aligned} X_m &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pi \frac{m}{N} n\right) \\ X_{N-m} &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pi \frac{N-m}{N} n\right) \\ &= \sum_{n=0}^{N-1} x_n \exp\left(-j2\pi n + j2\pi \frac{m}{N} n\right) \\ &= \sum_{n=0}^{N-1} x_n \exp\left(j2\pi \frac{m}{N} n\right) \\ &= (X_m)^* \end{aligned}$$

$$\begin{aligned} X_m &= a_k(\cos(\phi_k) - i \sin(\phi_k)) \\ (X_m)^* &= a_k(\cos(\phi_k) + i \sin(\phi_k)) \end{aligned}$$

Practice: Discrete Fourier Transform (DFT)

- Colab Practice!
- Example of DFT:
 - $f(t) = 10 \sin(2\pi 10t) + 3 \sin(2\pi 100t)$

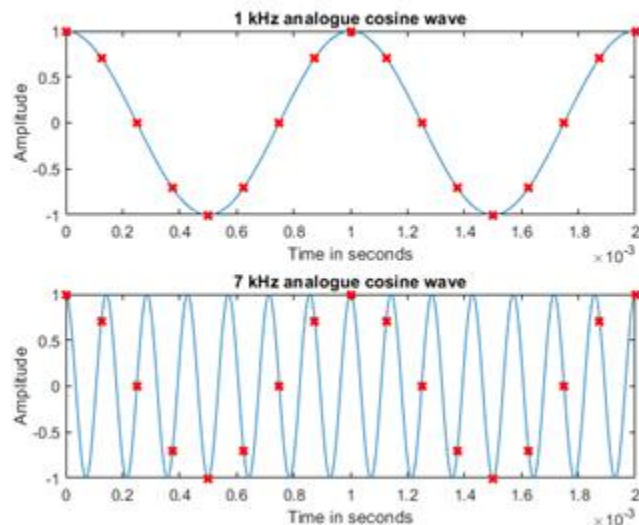


Discrete Fourier Transform (DFT)

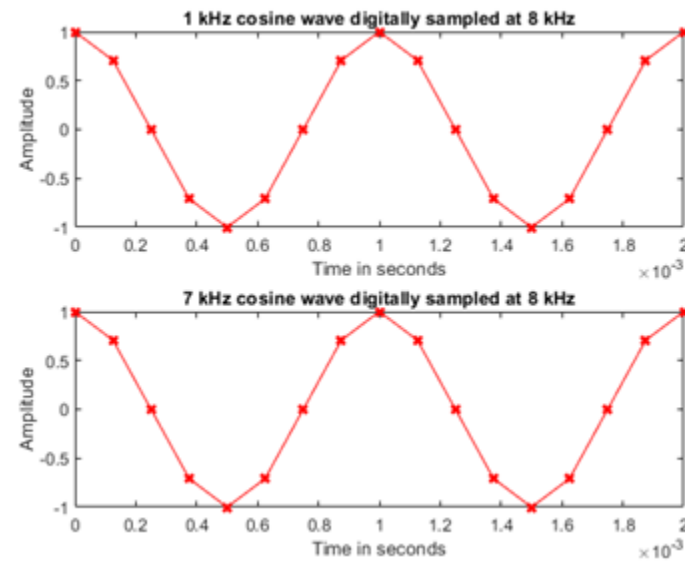
- Nyquist(나이퀴스트) Theorem:
 - If a function $f(t)$ contains no frequencies higher than B hertz, it is completely determined by giving its ordinates at series of points spaced $1/2B$ (**Nyquist frequency**) seconds apart (함수 $f(t)$ 가 B 헤르츠보다 높은 주파수를 포함하지 않는다면, $1/2B$ 초 간격으로 주어진 함수값 만으로도 완전히 결정할 수 있다.)
 - E.g., If signal contains frequency 100 Hz , you need to sample at 200 Hz at least to observe this frequency component
 - DFT of a segment of a signal with sample rate B , will produce amplitudes for nfft evenly spread frequencies in range $[-B/2; B/2]$

Discrete Fourier Transform (DFT)

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Aliasing!

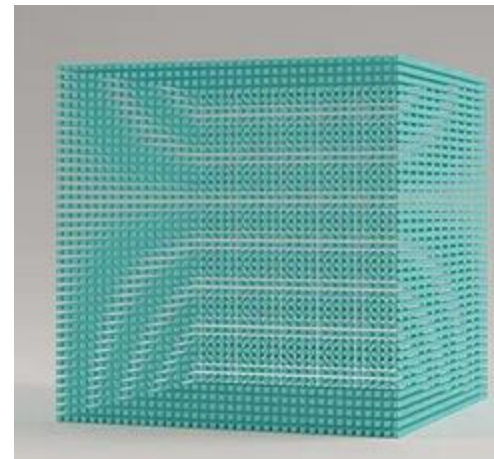


Discrete Fourier Transform (DFT)

https://en.wikipedia.org/wiki/Moir%C3%A9_pattern#

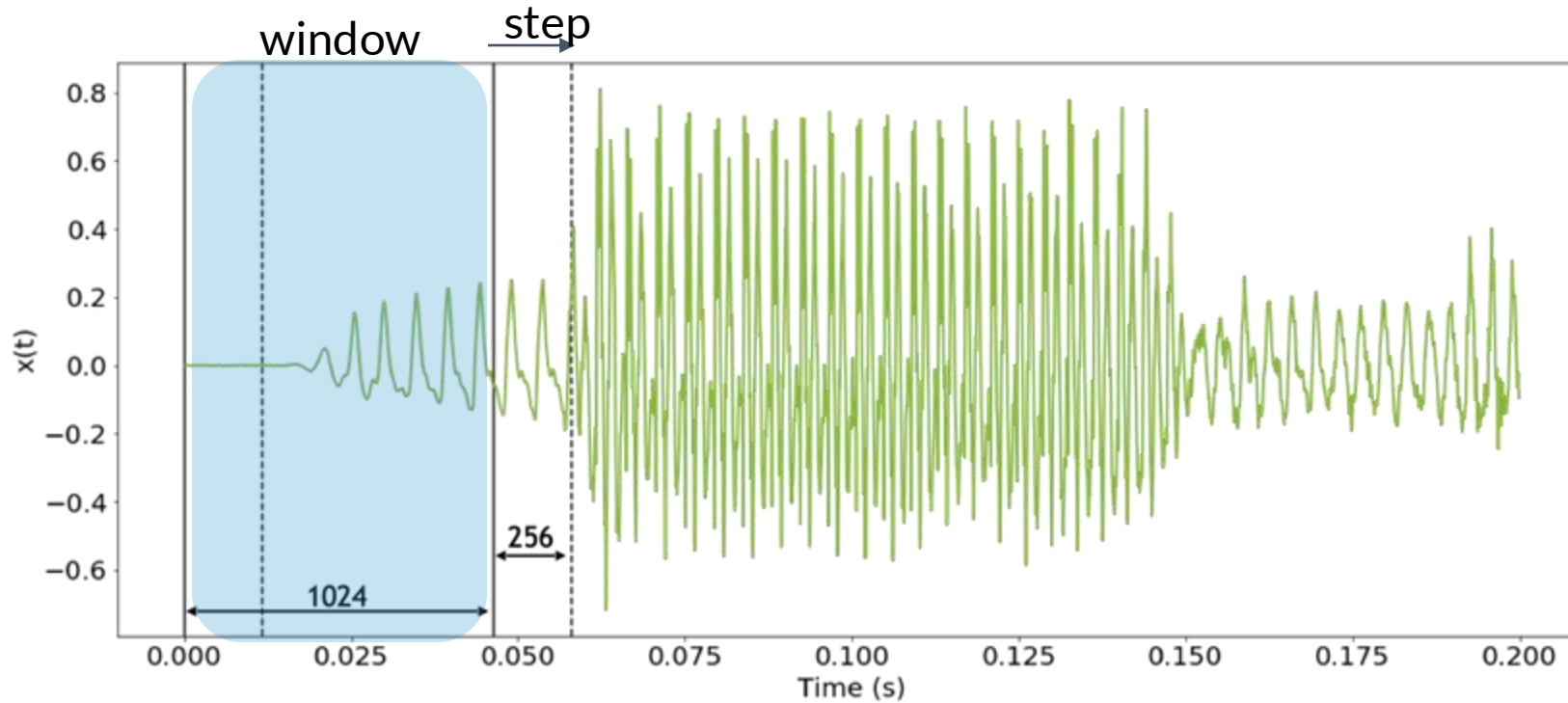
<https://www.adobe.com/creativecloud/photography/discover/anti-aliasing.html>

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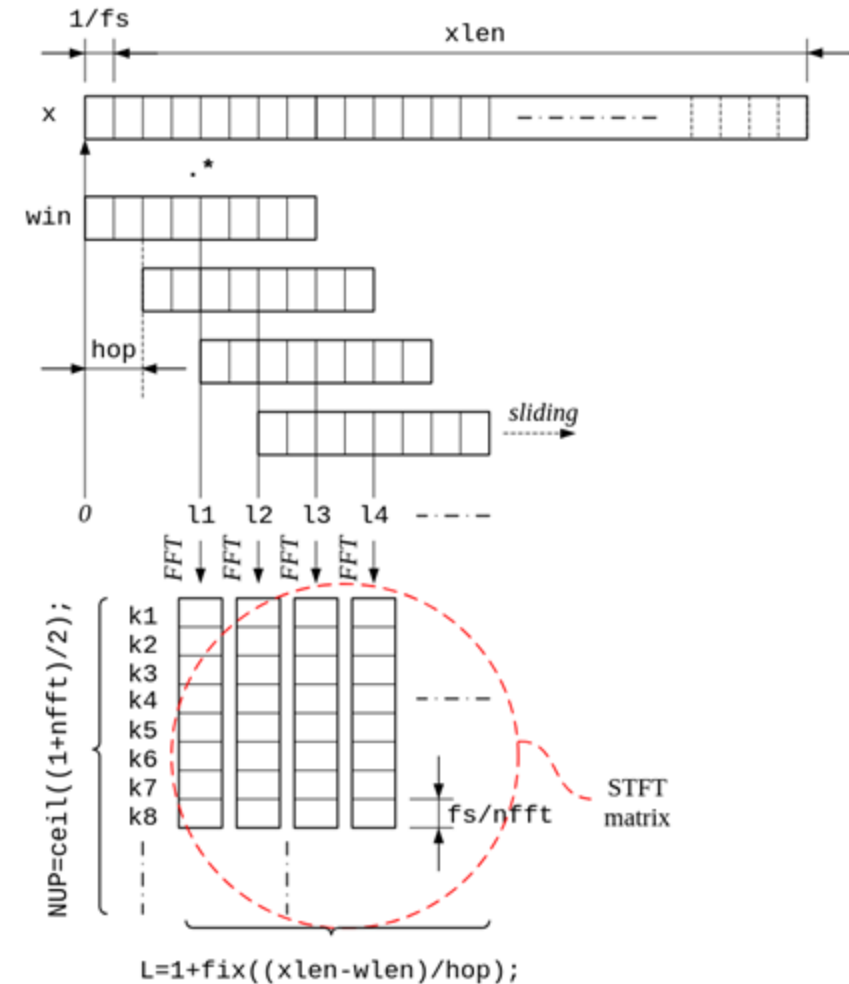
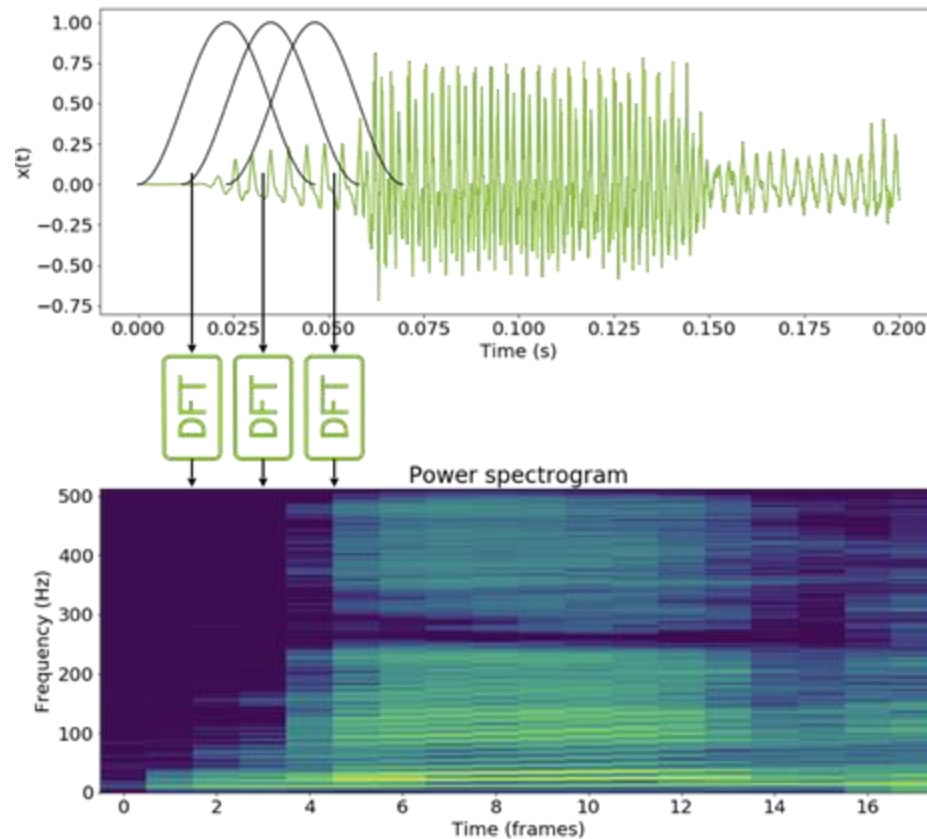
Aliasing effect in images

Shor-Time Fourier Transform



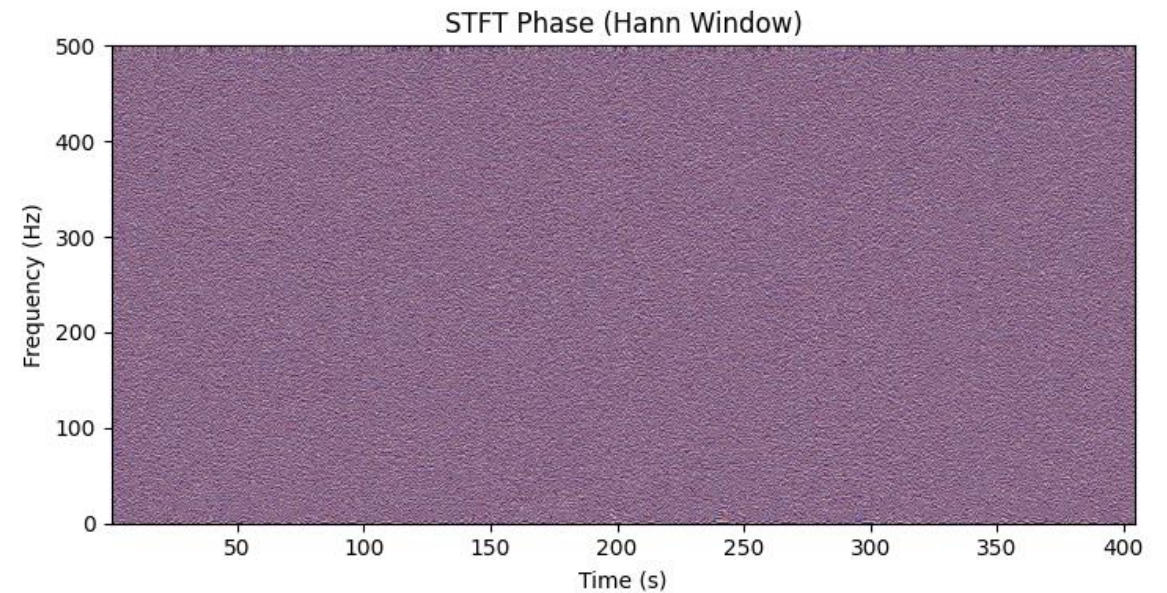
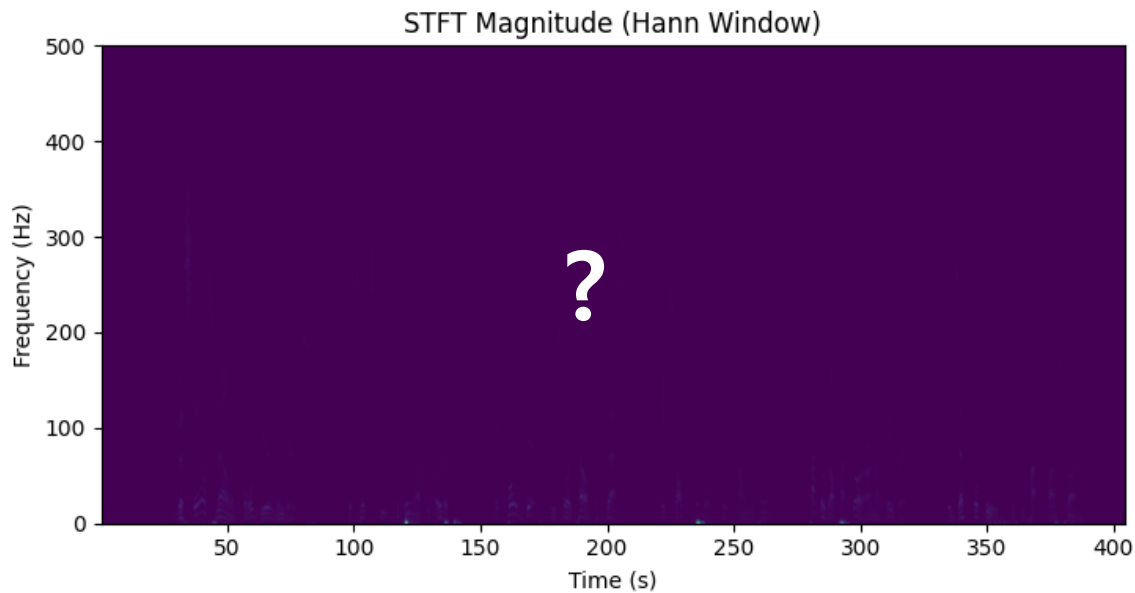
Shor-Time Fourier Transform

- STFT + Window function



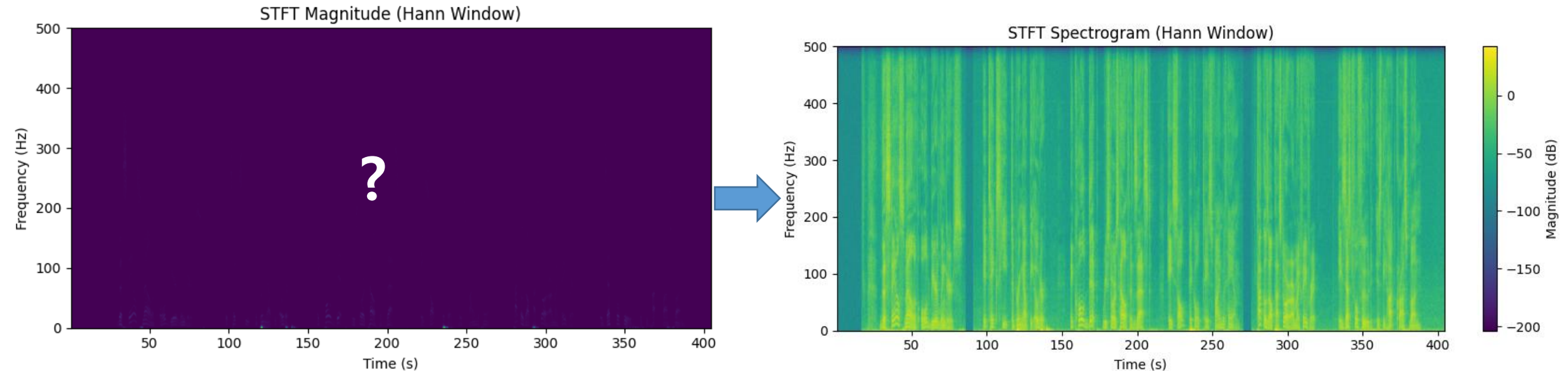
Shor-Time Fourier Transform

- Spectrogram:
 - The output of STFT is a complex matrix of size $n\text{Freq} * n\text{Windows}$
 - Useually, we look at magnitude and phase of the output



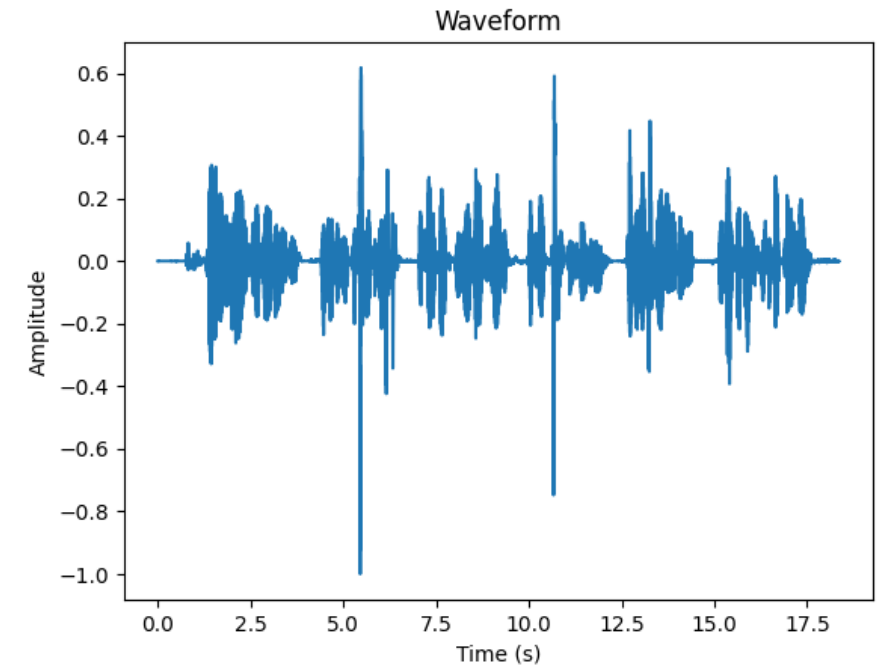
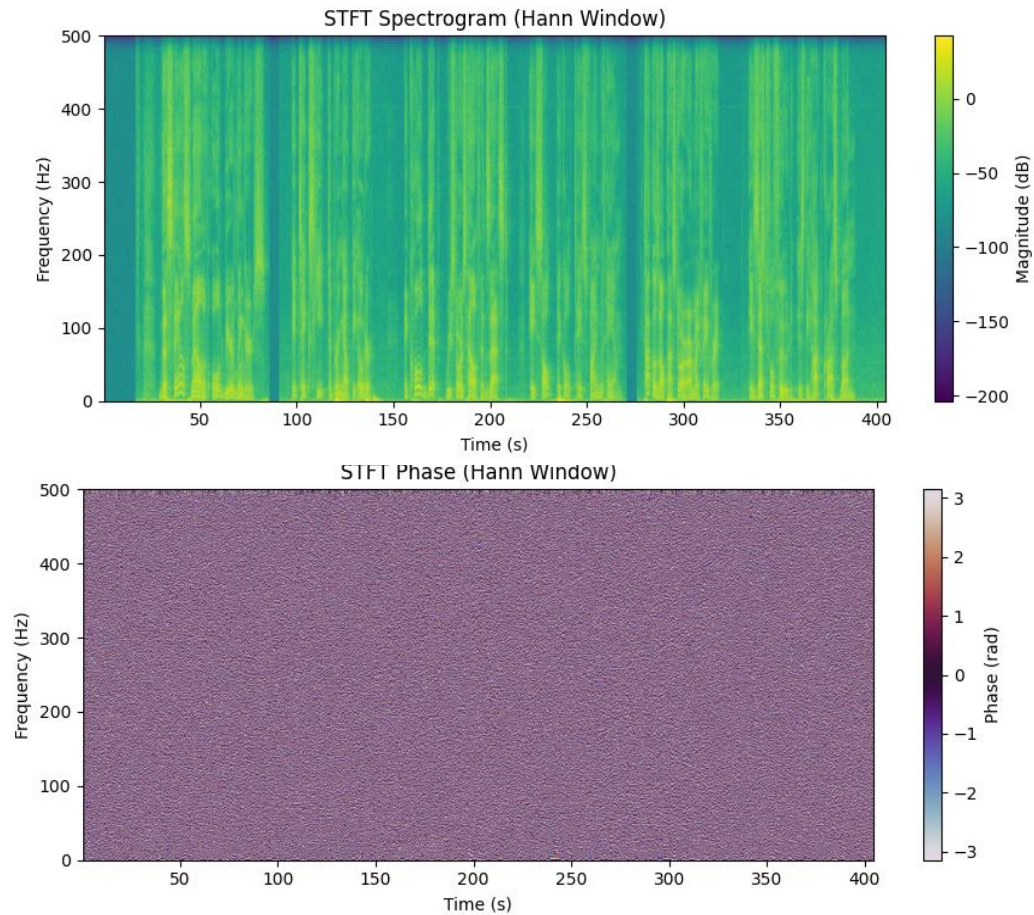
Shor-Time Fourier Transform

- Spectrogram:
 - The logarithm of the magnitude spectrogram is much easier visually to interpret



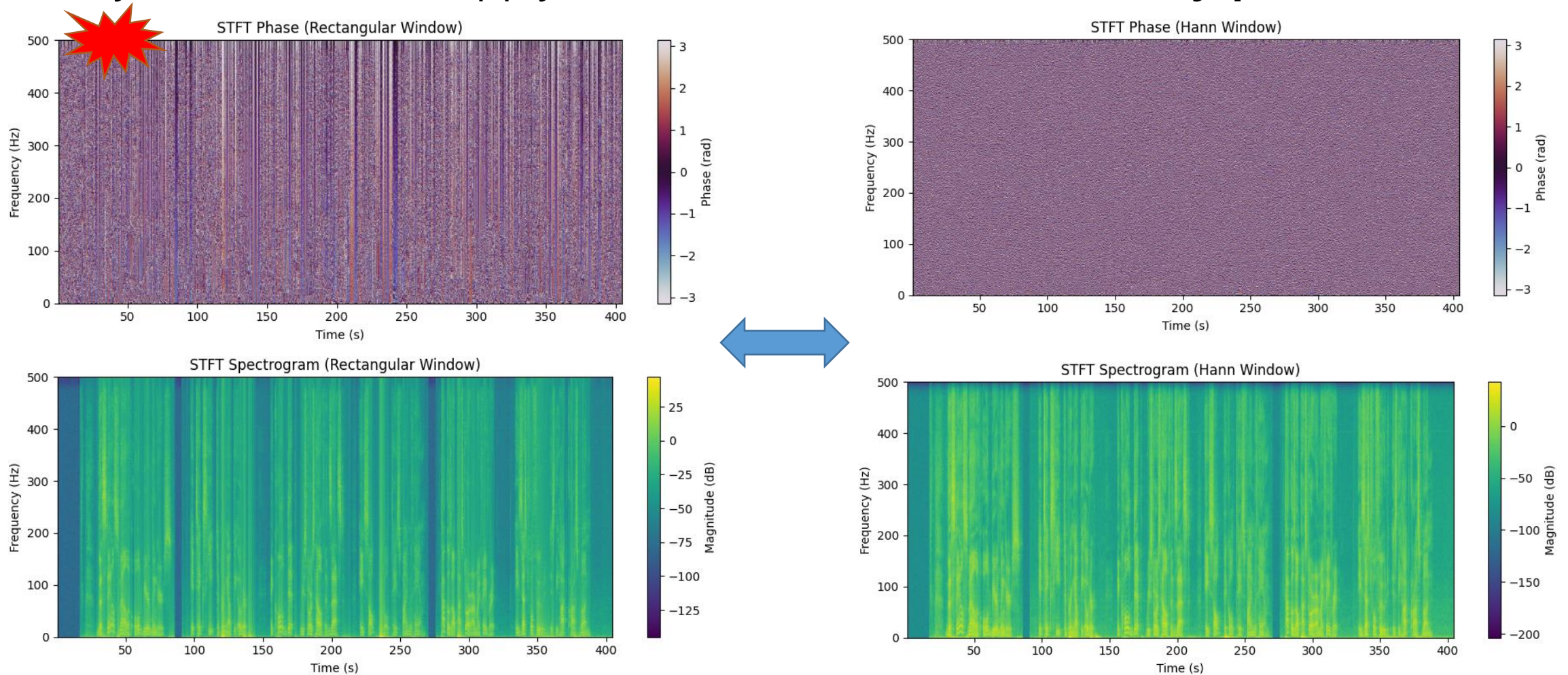
Shor-Time Fourier Transform

- Inver STFT (iSTFT)
 - STFT result can be inverted back given the parameters are known (window, hop and step sizes)



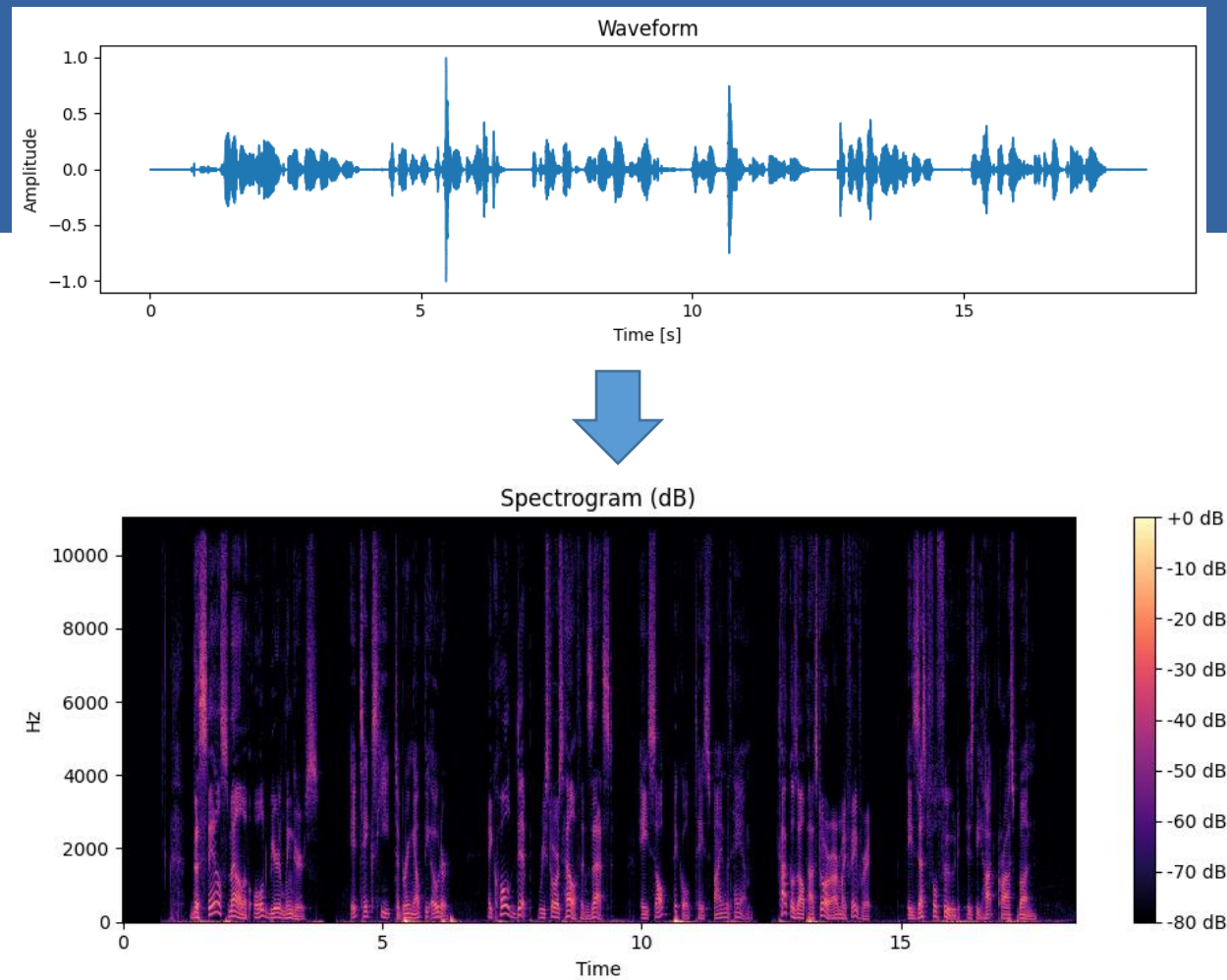
Shor-Time Fourier Transform

- Why do we have to apply window functions: **discontinuity problem!**



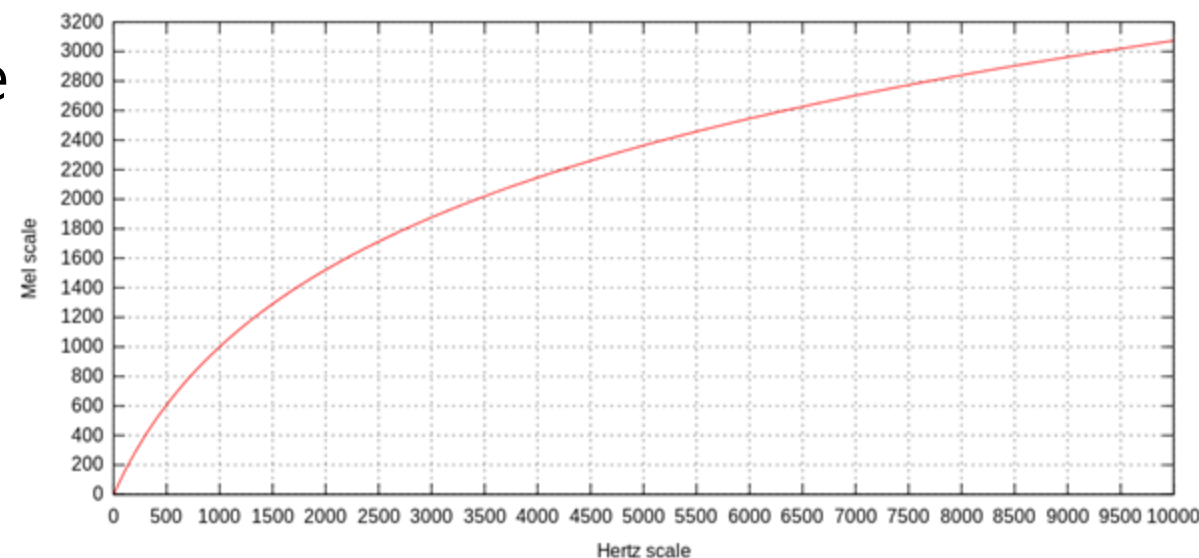
Practice!

- Colab practice!



Mel Spectrogram

- 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:

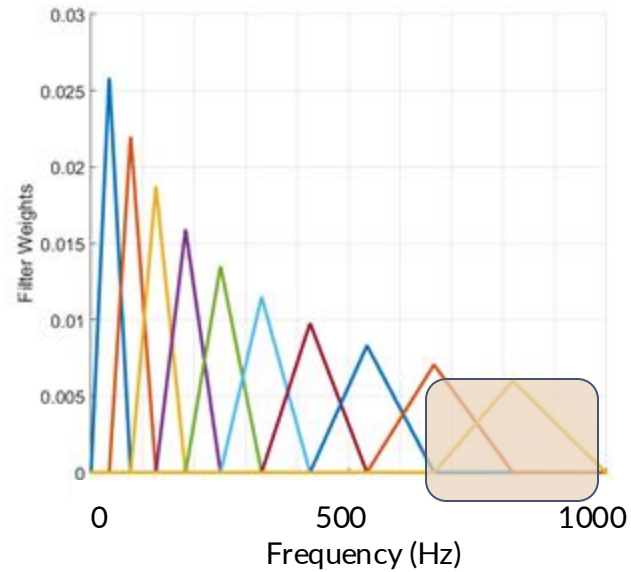
$$m = 2595 \log_{10} \left(1 + \frac{f}{700} \right) = 1127 \ln \left(1 + \frac{f}{700} \right)$$

The corresponding inverse expressions are:

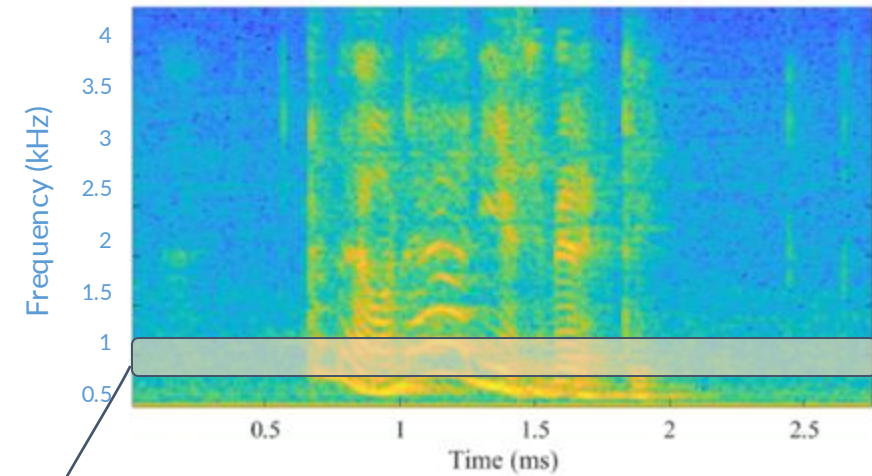
$$f = 700 \left(10^{\frac{m}{2595}} - 1 \right) = 700 \left(e^{\frac{m}{1127}} - 1 \right)$$

Mel Spectrogram

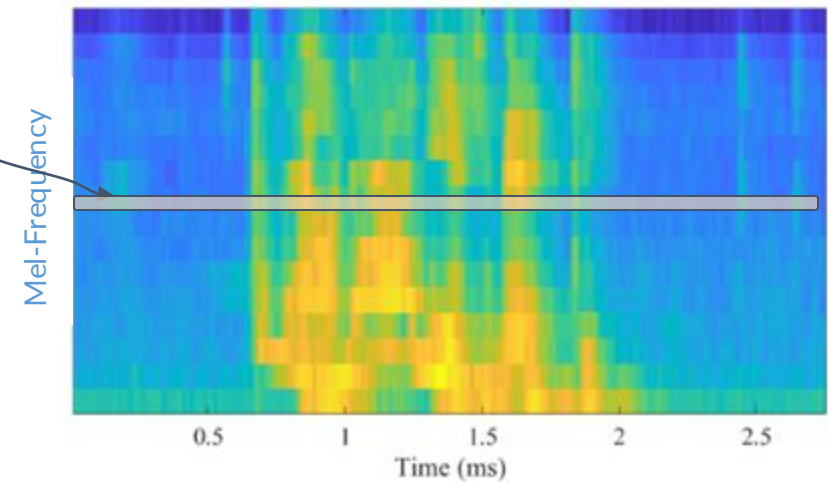
- Mel Spectrogram



Spectrogram of a segment of speech

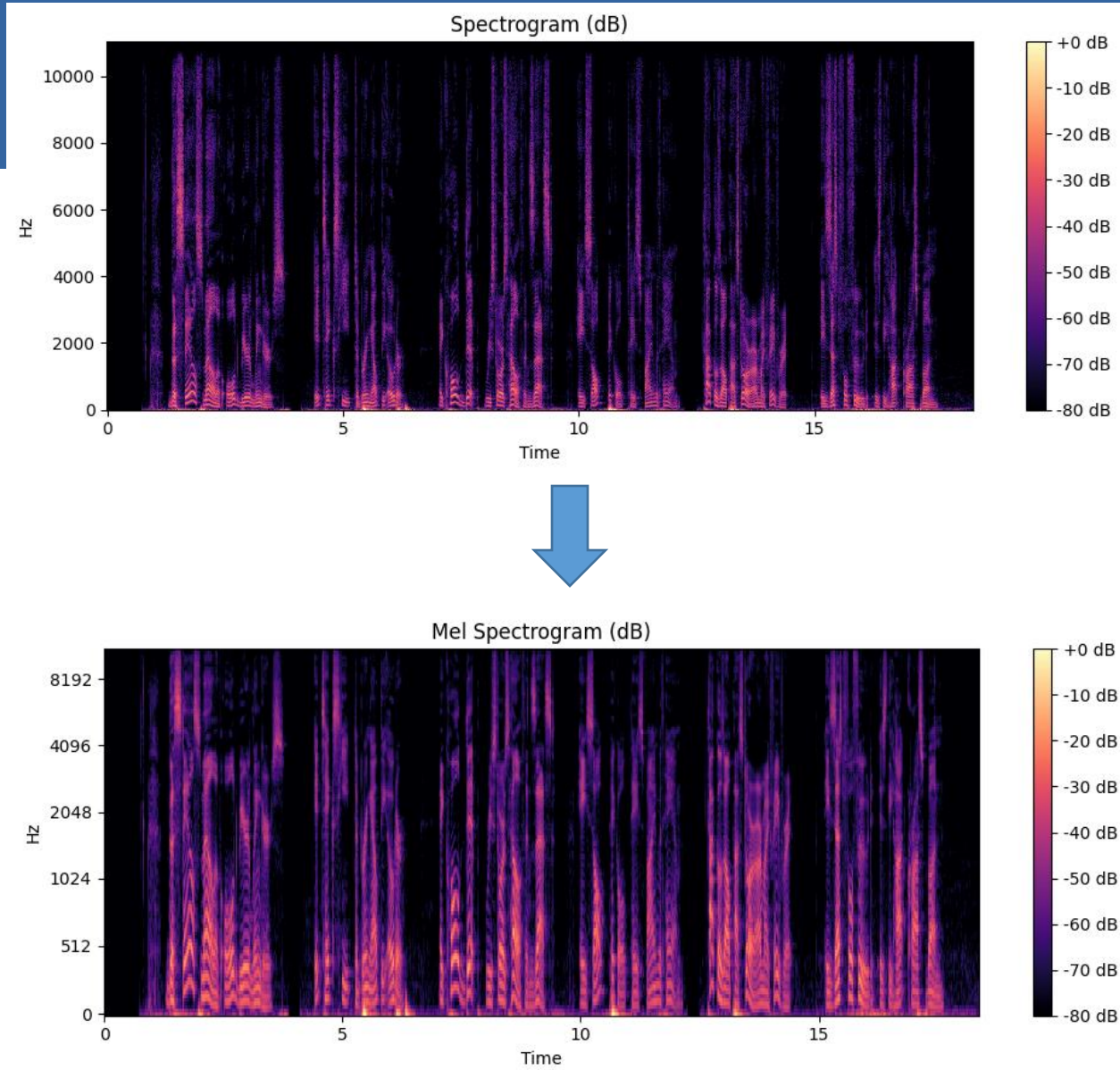


Spectrogram after multiplication with mel-weighted filterbank



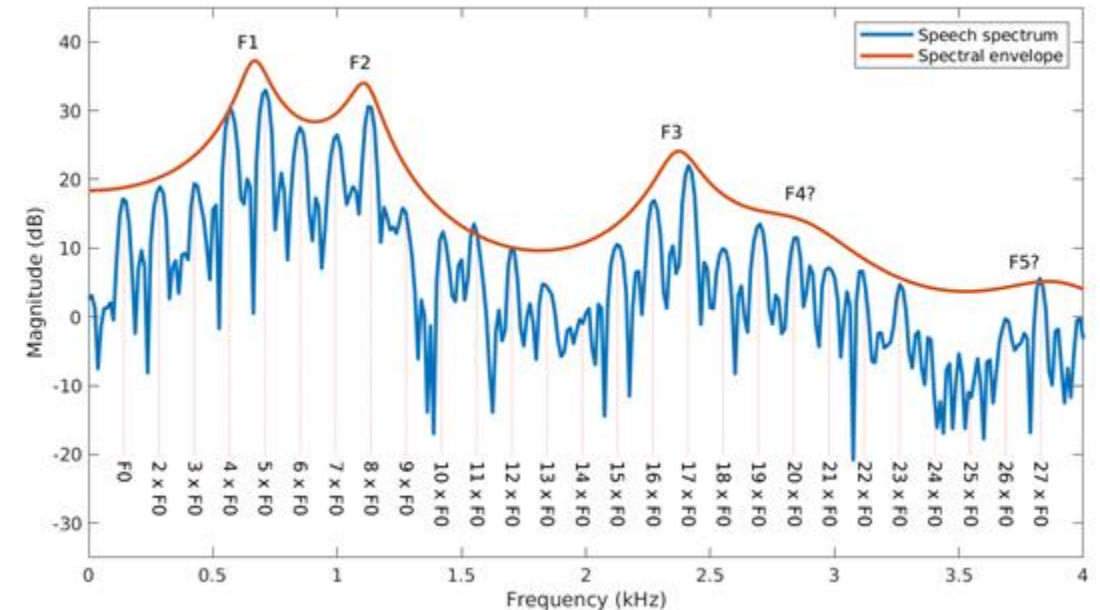
Practice!

- Colab practice!



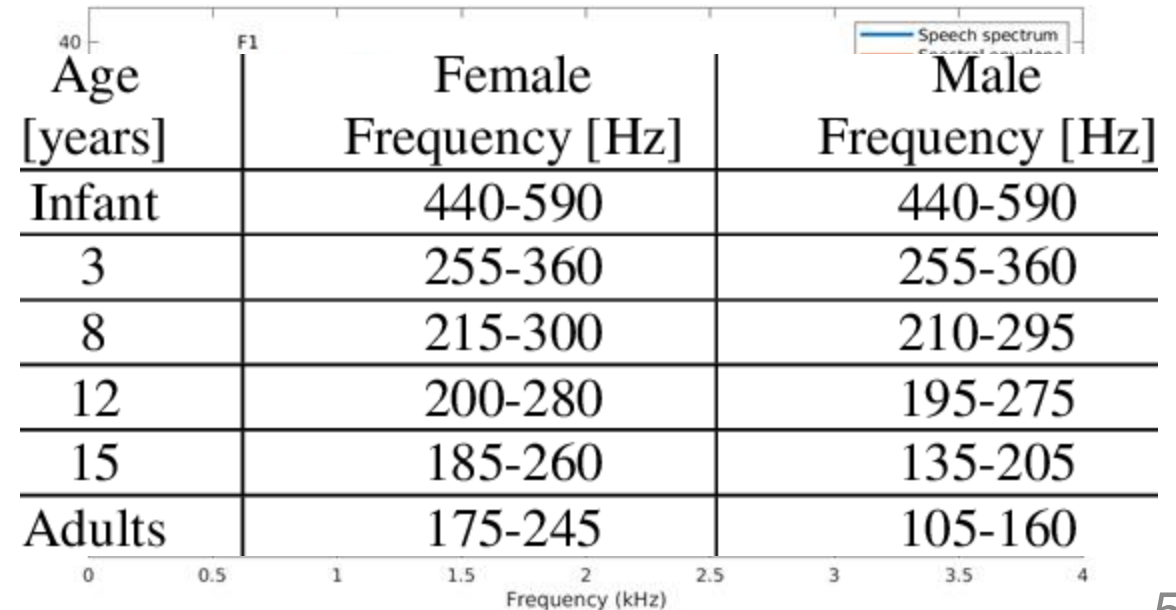
MFCC

- Fundamental frequency is the physical source frequency, but there are **resonances** (공진) and **harmonics** (배음)
- Peaks on envelope curve are **formants**
- Pitch is perceptual value, **F0 is physical**, **harmonics are $k \times F0$**
- For speech F0 lie roughly in the range 80 to 450 Hz, typically males have lower voices than females and children



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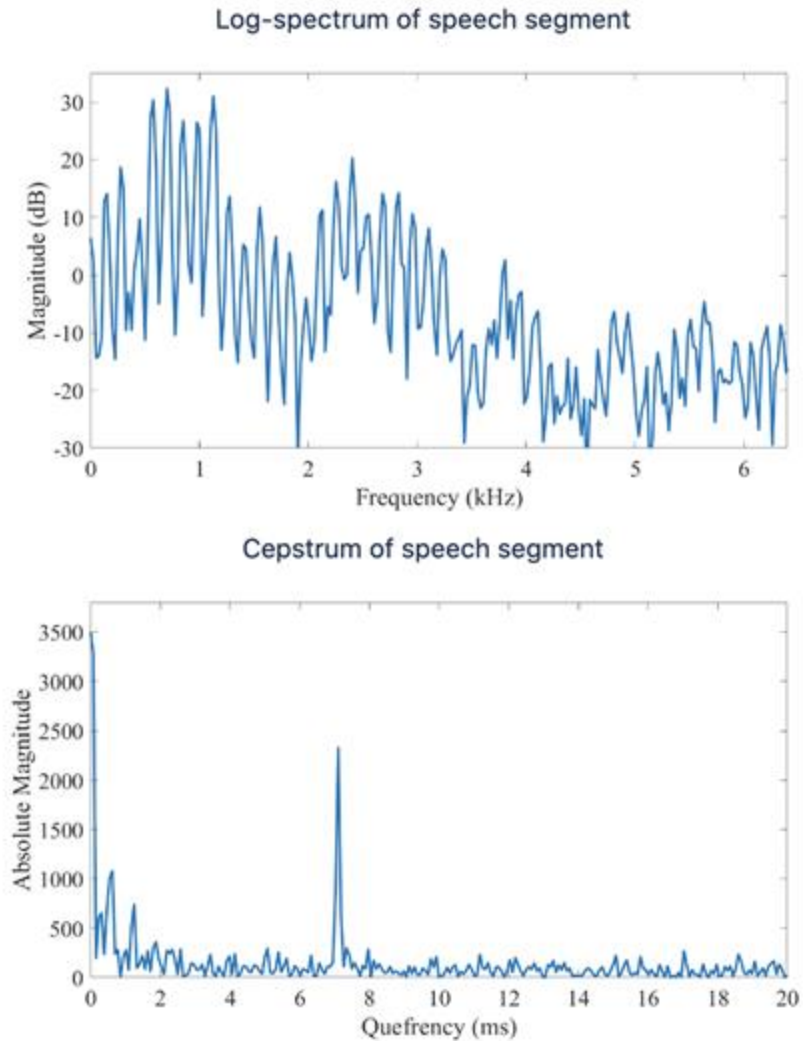


MFCC

- Cepstrum

- Fourier spectrum of voice has periodic structure
- Apply Inverse DFT to log-spectrum ($\log|X(\omega)|$) and obtain Cepstrum
- Peak in Cepstrum should be located at $\frac{1}{F_0}$

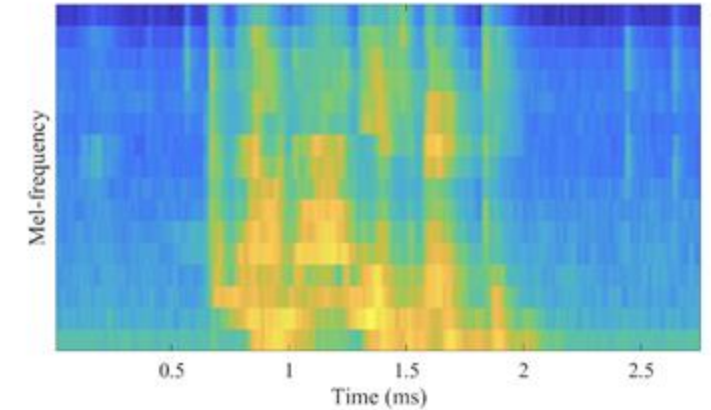
왜 이럴까?



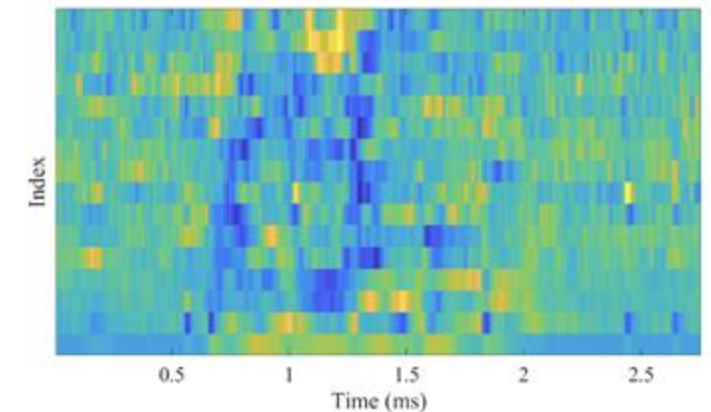
MFCC

- Mel-Frequency Cepstral Coefficient (MFCC)
 - Apply STFT to the signal
 - Apply mel filters
 - Take the log value
 - Apply Discrete Cosine Transform

Spectrogram after multiplication with mel-weighted filterbank



Corresponding MFCCs



Practice!

- Colab practice!

