

PAT 498/598 (Winter 2025)

# Music & AI

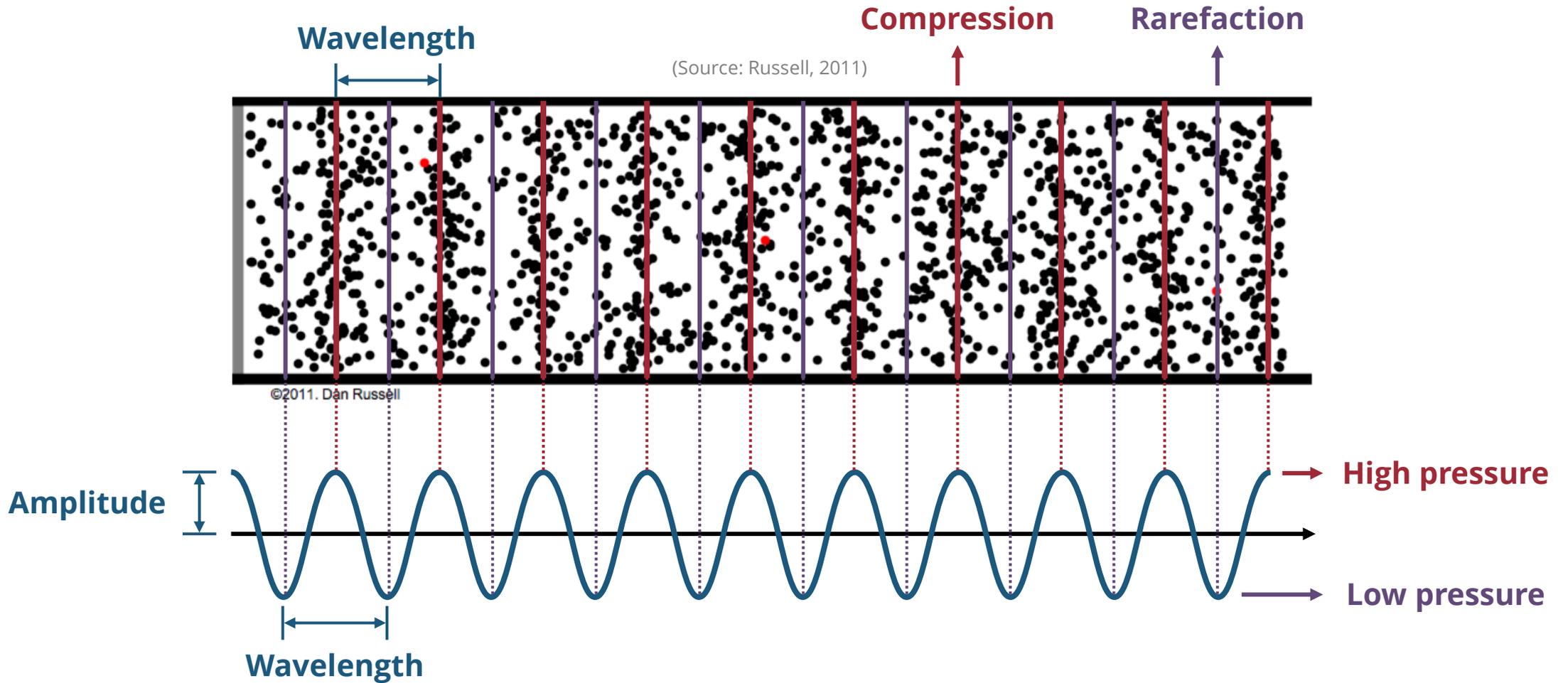
## Lecture 6: Spectral Analysis

Instructor: Hao-Wen Dong

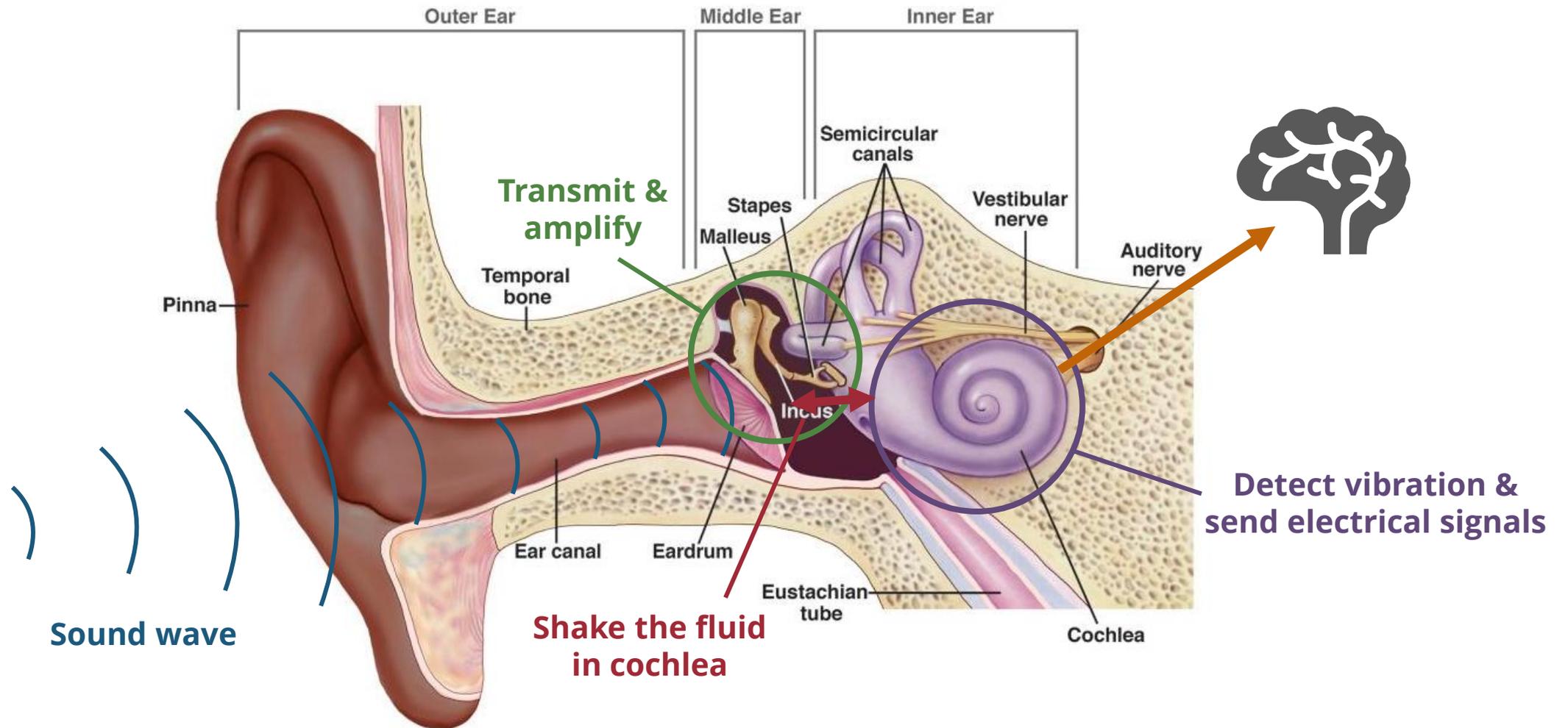


SCHOOL OF MUSIC, THEATRE & DANCE  
PERFORMING ARTS TECHNOLOGY  
UNIVERSITY OF MICHIGAN

# (Recap) Longitudinal vs Transverse Waves



# (Recap) Human Ears



(Source: NIH/NIDCD)

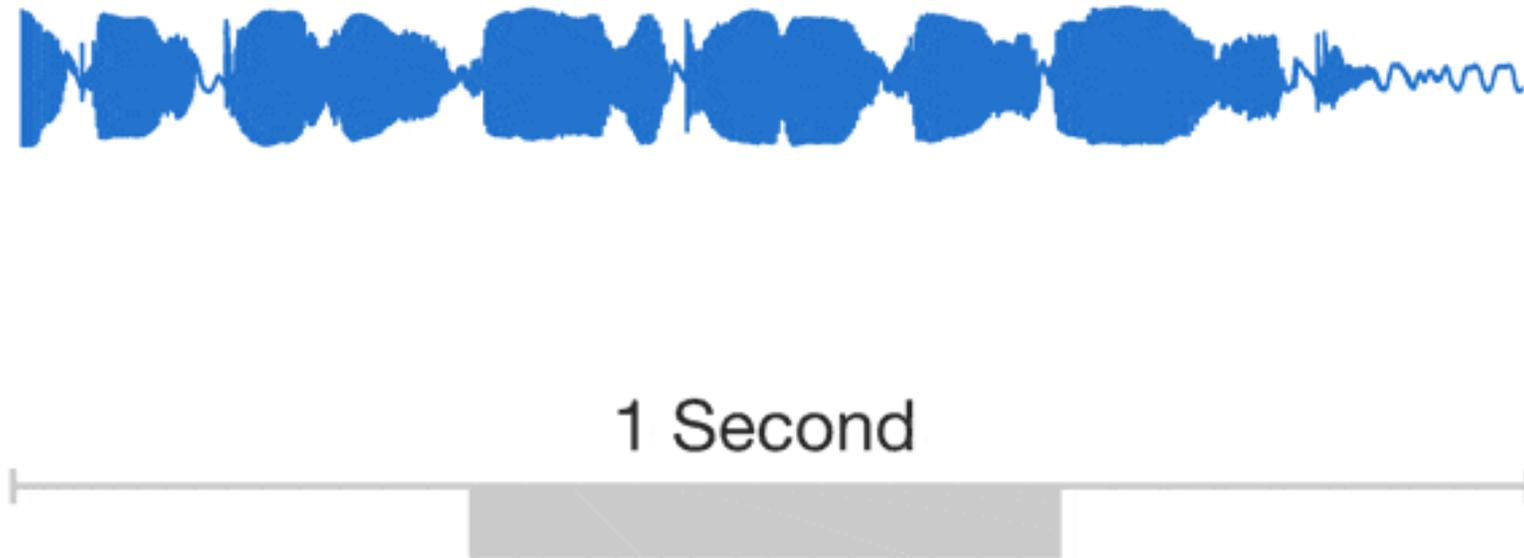
## (Recap) Sound **Intensity** & Decibels

- **Sound intensity** is defined as the sound power per unit area
  - Usually measured in **watt per square meter** ( $\text{W}/\text{m}^2$ )
- **Sound intensity level** is defined as

$$I_{\text{dB}} := 10 \log_{10} \left( \frac{I}{I_{\text{REF}}} \right)$$

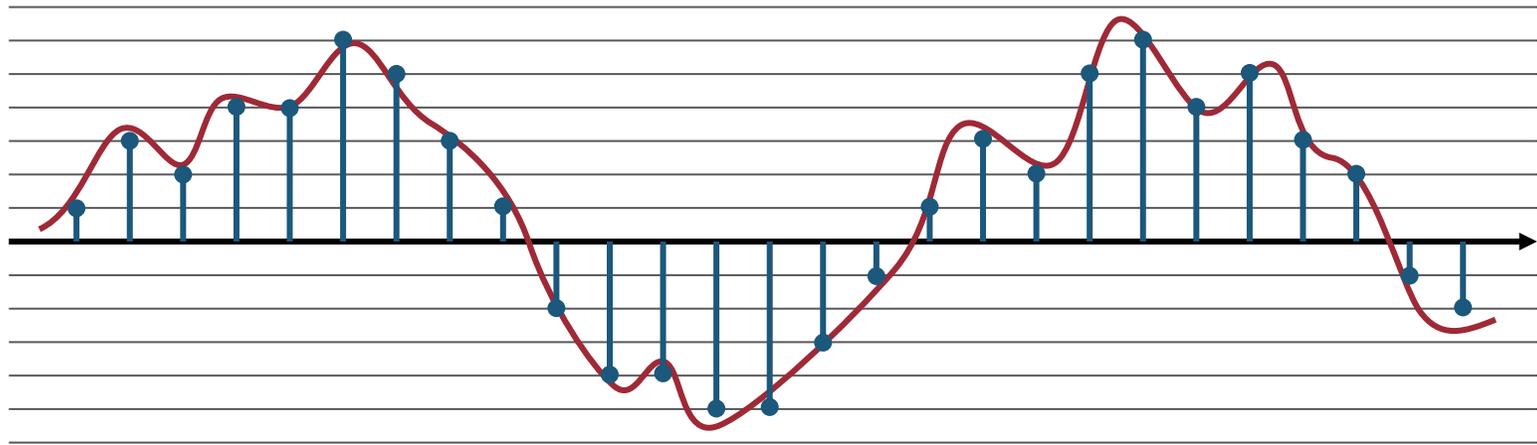
- $I_{\text{REF}} := 10^{-12} \text{W}/\text{m}^2$  is the **threshold of hearing** (TOH)
- TOH: minimum sound intensity of a pure tone that a human can hear

# (Recap) Digital Audio

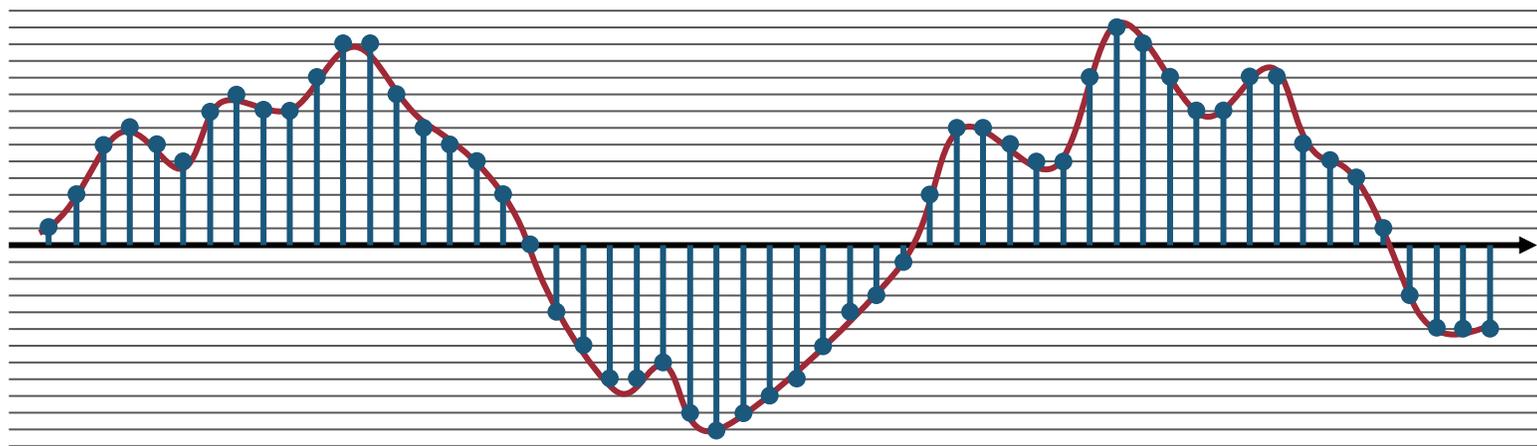


(Source: van den Oord et al., 2016)

# (Recap) Resolution: Sampling Rate & Bit Depth



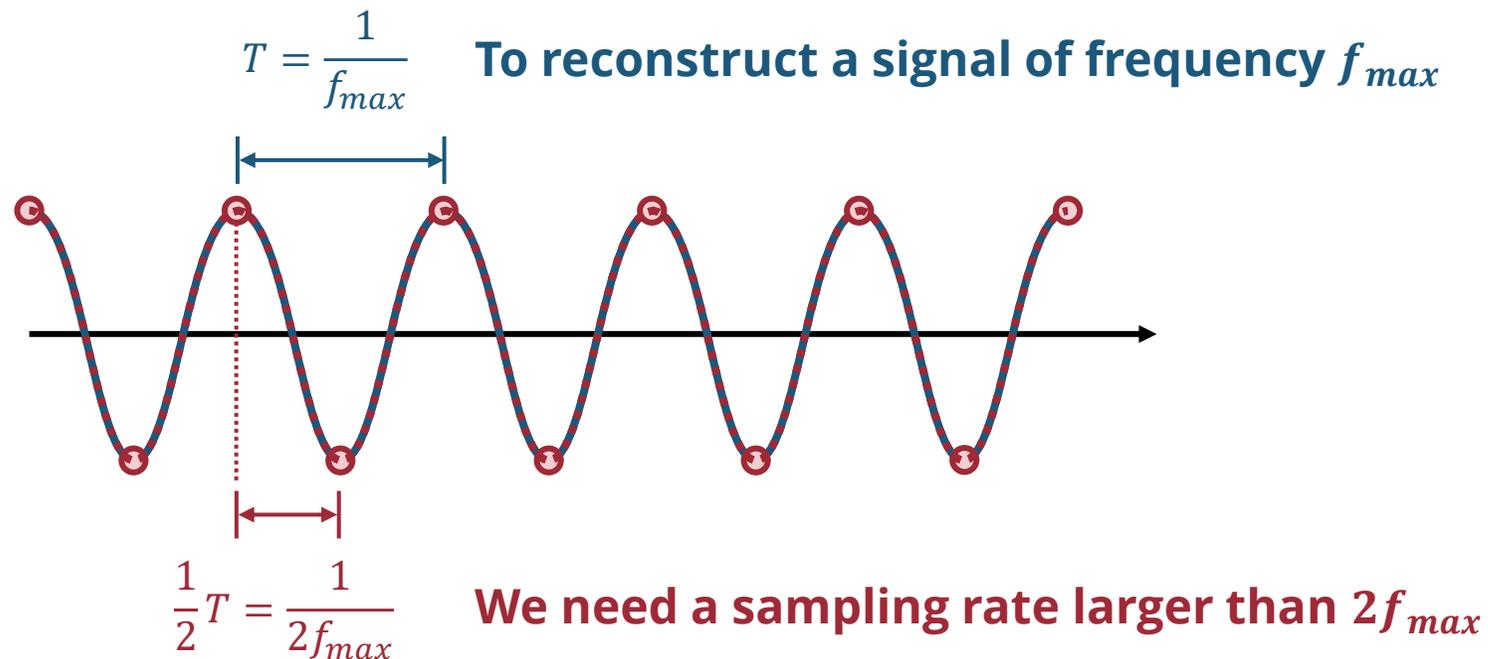
Double the **sampling rate** & **bit depth**



# Sampling Theorem

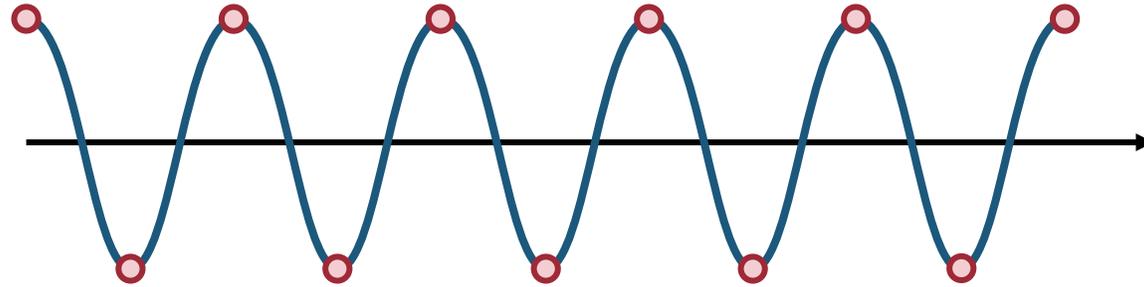
# Nyquist–Shannon Sampling Theorem

- **Theorem:** If a signal contains no frequencies higher than  $f_{max}$ , then the signal can be perfectly reconstructed when sampled at a rate  $f_s > 2f_{max}$ 
  - $2f_{max}$  is usually referred to as the **Nyquist rate**

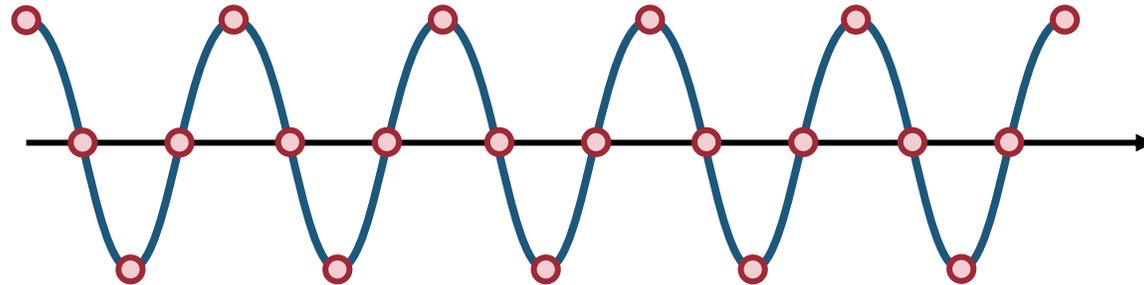


# Sampling Theorem: Oversampling

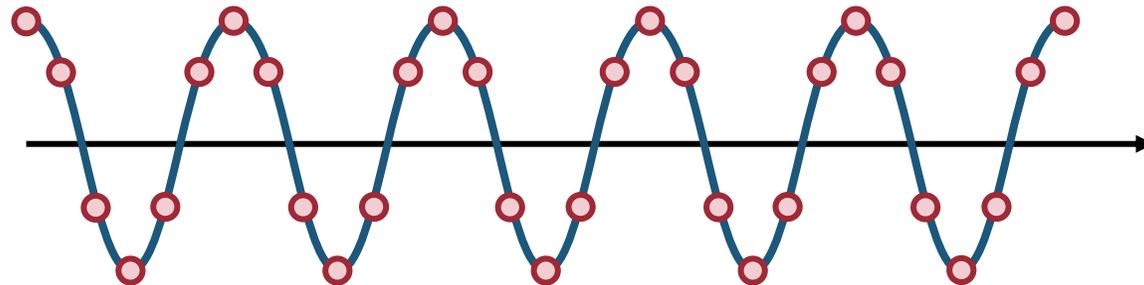
**Critically sampled**  
( $f_s = 2f_{max}$ )



**Oversampled**  
( $f_s = 4f_{max}$ )



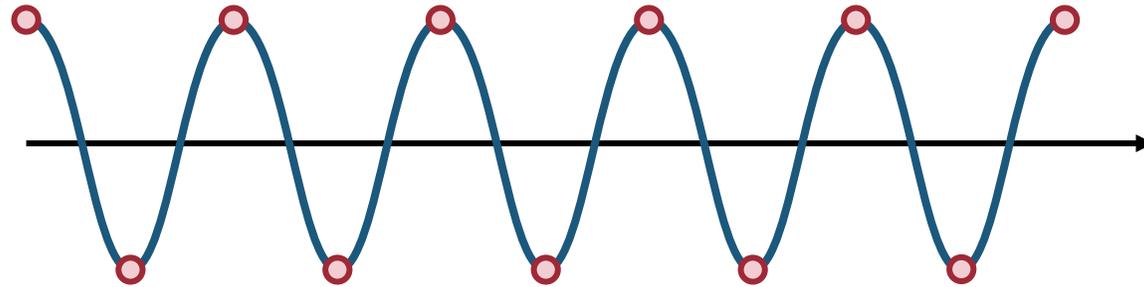
**Oversampled**  
( $f_s = 6f_{max}$ )



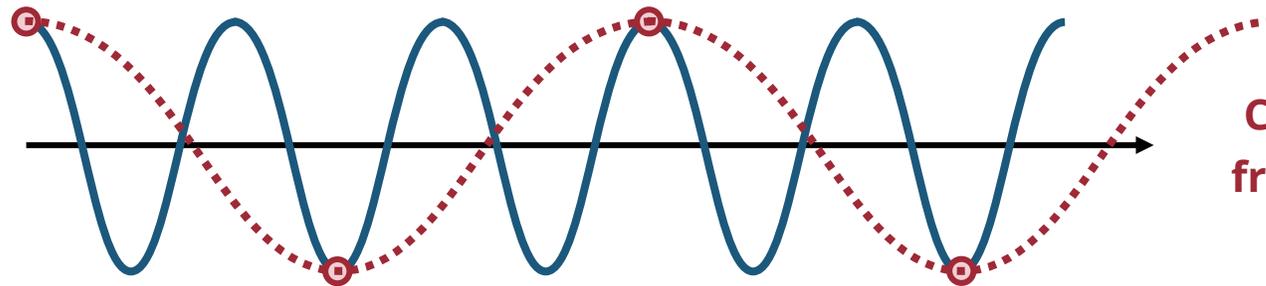
**Reconstruction  
is possible!**

# Sampling Theorem: Undersampling

**Critically sampled**  
( $f_s = 2f_{max}$ )

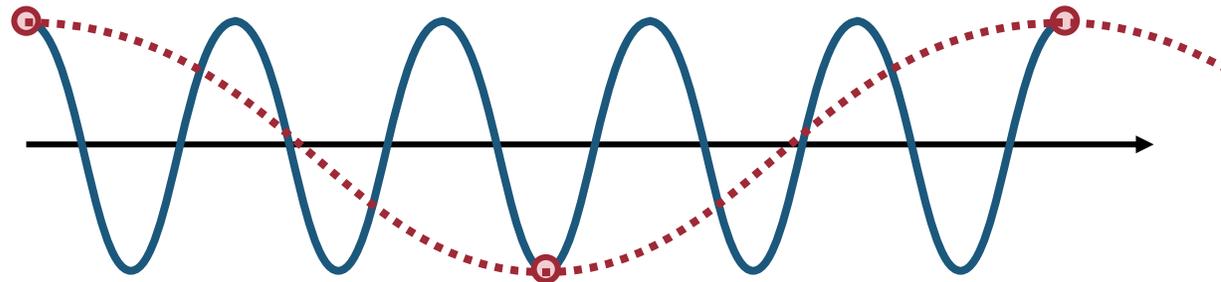


**Undersampled**  
( $f_s = \frac{2}{3}f_{max}$ )



Can only reconstruct  
frequency up to  $\frac{1}{3}f_{max}$

**Undersampled**  
( $f_s = \frac{2}{5}f_{max}$ )



Can only reconstruct  
frequency up to  $\frac{1}{5}f_{max}$

# Sampling Theorem

- Telephone audio is sampled at 8 kHz. What is the maximum frequency it can reconstruct?
- To cover the **human hearing range (20Hz to 20 kHz)**, what is the minimum sampling rate required?

# Sampling Rate & Frequency Range

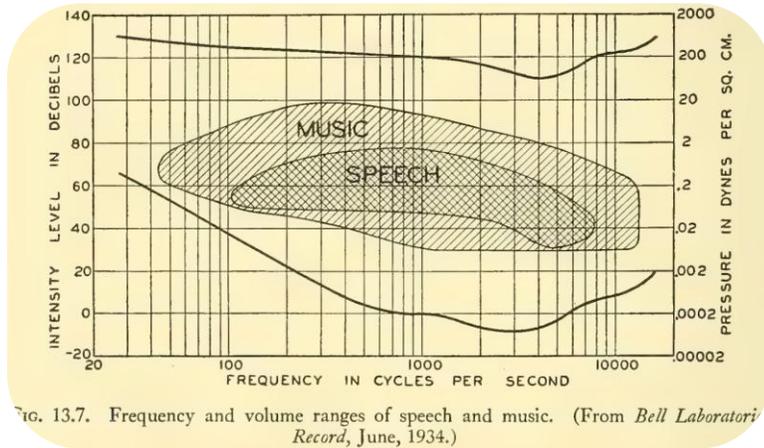
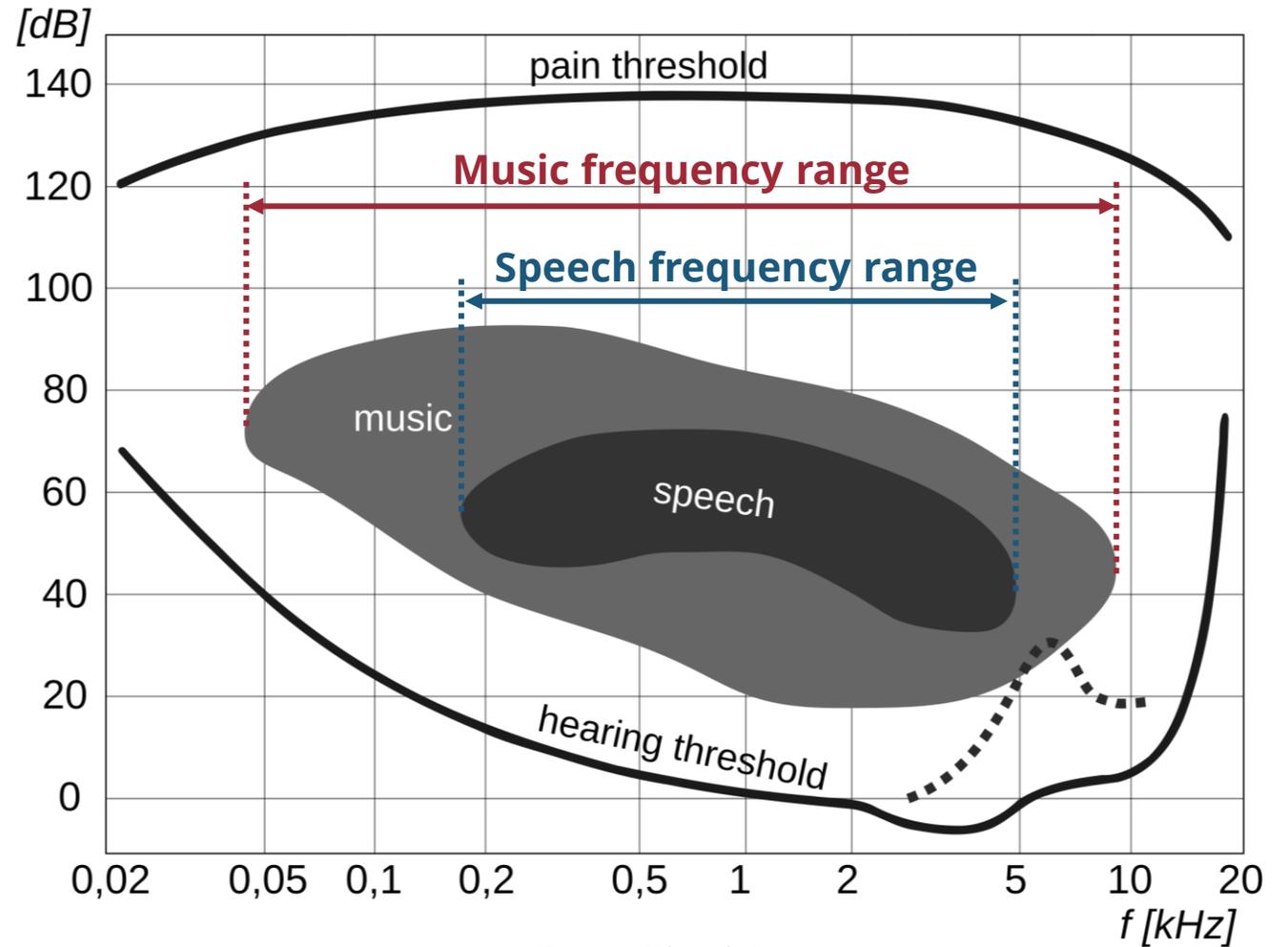


FIG. 13.7. Frequency and volume ranges of speech and music. (From *Bell Laboratories Record*, June, 1934.)

(Source: Bell Laboratories Record 1934 & Olson 1947)



(Source: Wikipedia)

*Bell Laboratories Record*, 12(6):314, 1934.

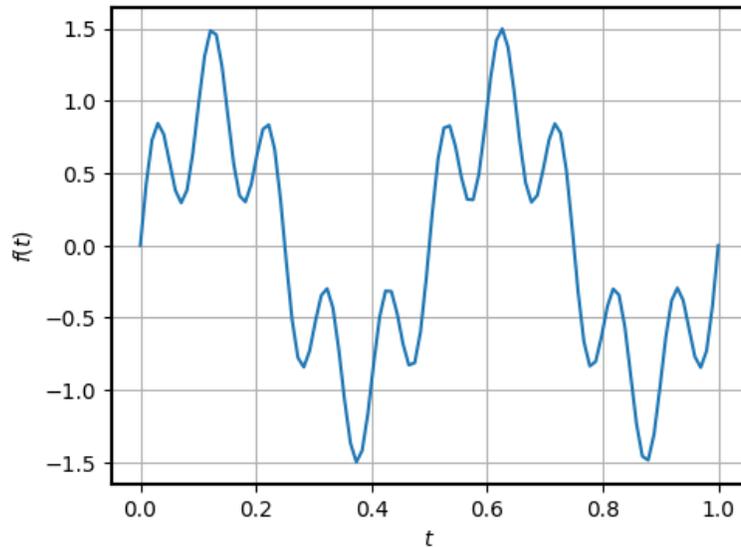
Harry Ferdinand Olson, "Speech, Music and Hearing," *Elements of acoustical engineering Hardcover*, p. 326, 1947.

[en.wikipedia.org/wiki/Hearing\\_range](https://en.wikipedia.org/wiki/Hearing_range)

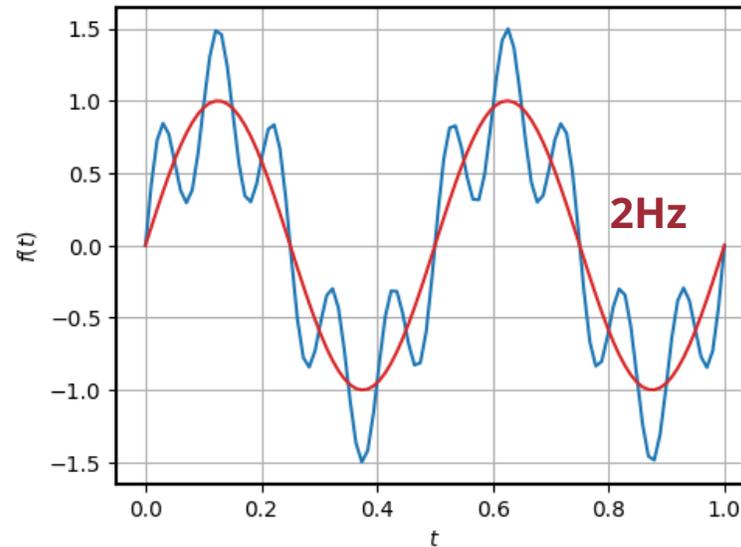
# Spectral Analysis

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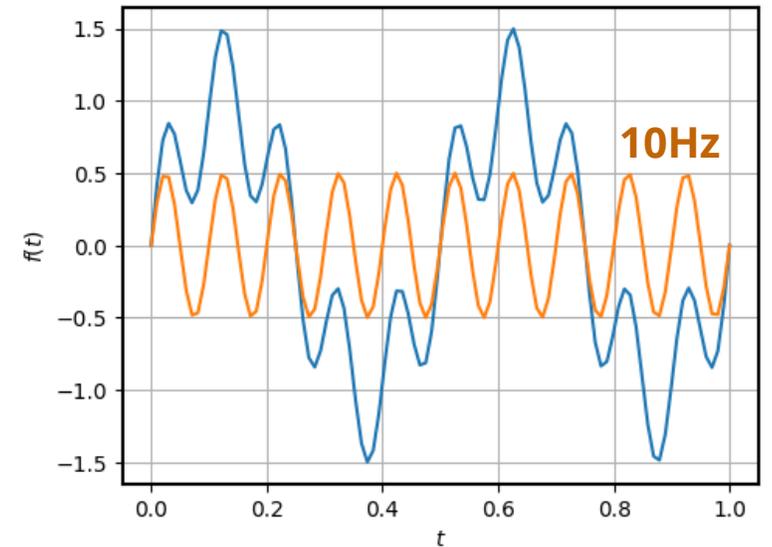
- **Goal:** Analyze the **frequency components** of a signal



$$\sin(2 \cdot 2\pi t) + \frac{1}{2} \sin(10 \cdot 2\pi t)$$

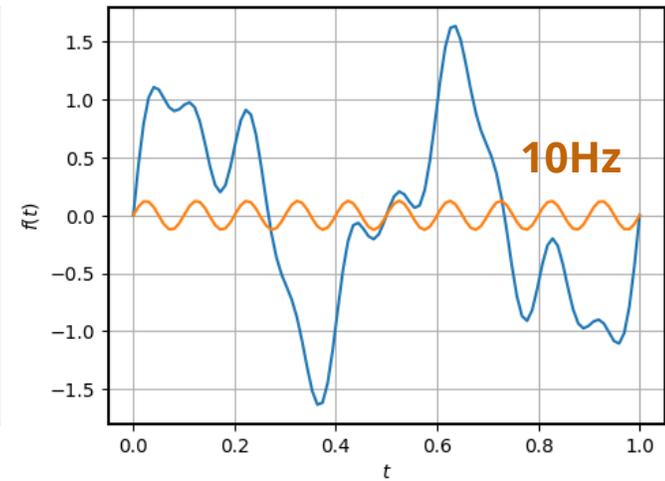
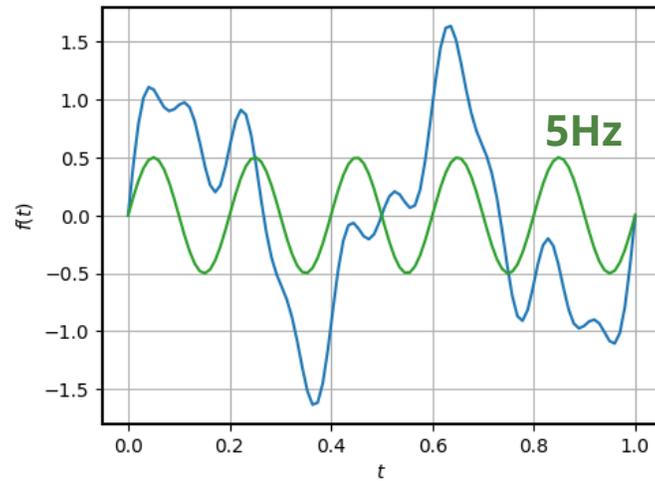
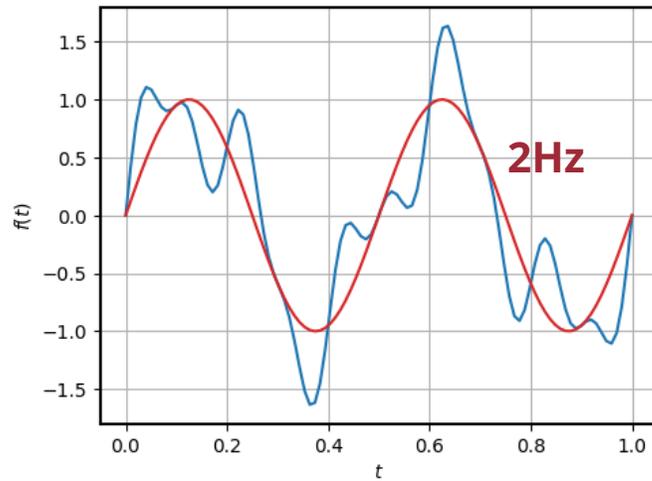
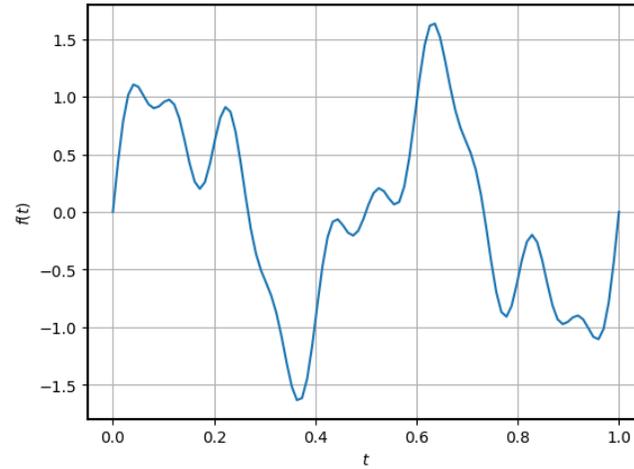


$$\sin(2 \cdot 2\pi t)$$



$$\frac{1}{2} \sin(10 \cdot 2\pi t)$$

# Spectral Analysis



# Fourier Transform

- **Intuition:** Decompose time-domain signals into **frequency components**
- Mathematical formulation:

The diagram illustrates the Fourier Transform equation with several annotations:

- Output spectrum:** A green box containing  $F(\omega)$  with an upward arrow pointing to the text "Output spectrum".
- Frequency:** An orange arrow points from the  $\omega$  in  $F(\omega)$  to the text "Frequency".
- Input signal:** A blue box containing  $f(t)$  with an upward arrow pointing to the text "Input signal".
- Sum over all  $t$ :** A purple arrow points from the integral symbol  $\int_{-\infty}^{\infty}$  to the text "Sum over all  $t$ ".
- Complex exponential:** A red box containing  $e^{-j\omega t}$  with a purple arrow pointing to it from the "Sum over all  $t$ " label. A thinking face emoji is placed above this box.
- Differential element:** A purple box containing  $dt$  with a purple arrow pointing to it from the "Sum over all  $t$ " label.

The equation is presented as: 
$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt$$

# Demystifying Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \boxed{e^{-j\omega t}} dt$$

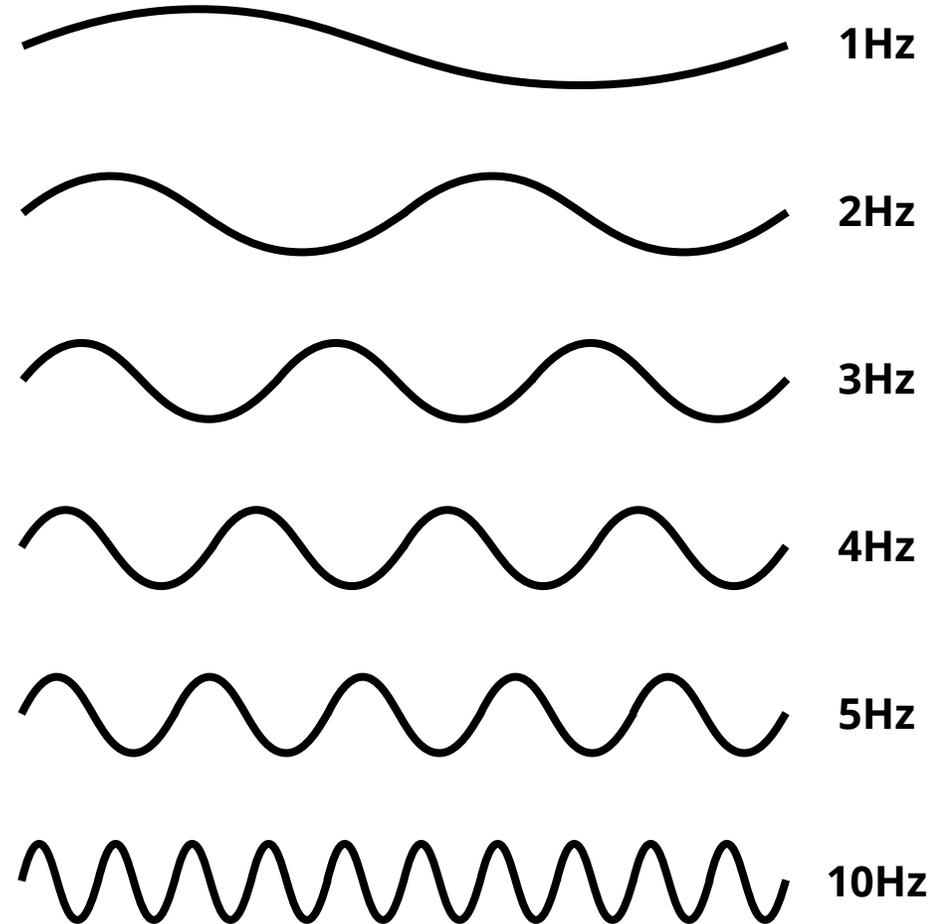
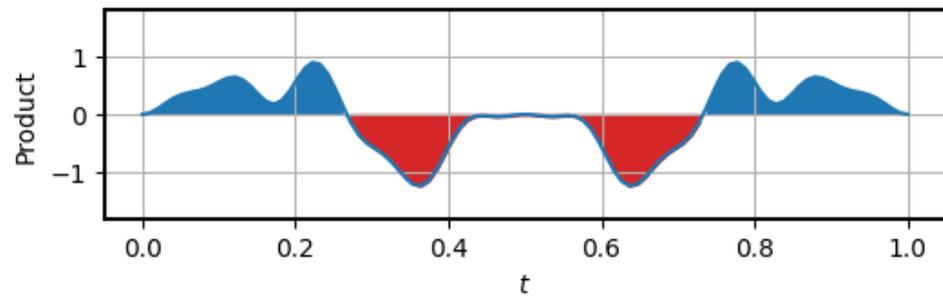
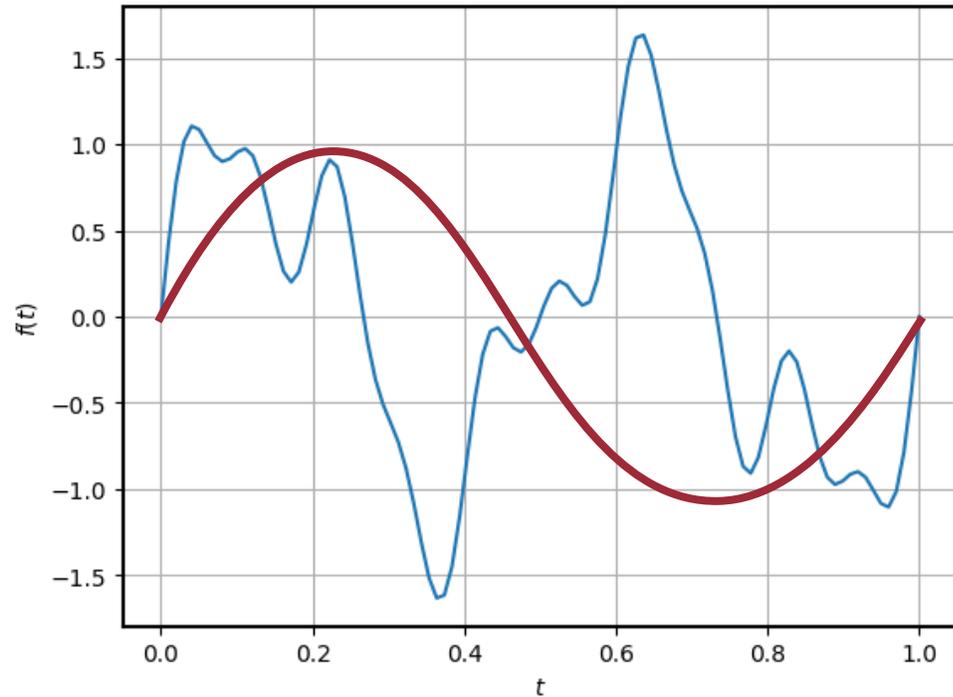



**Euler's formula**

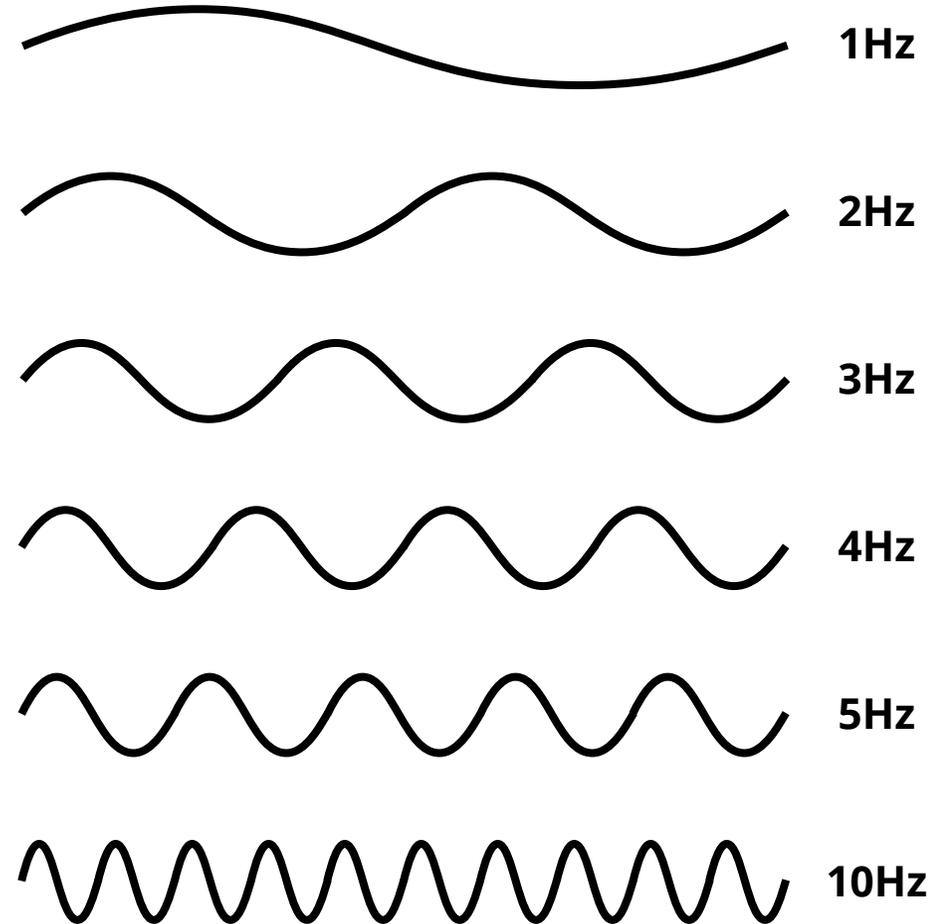
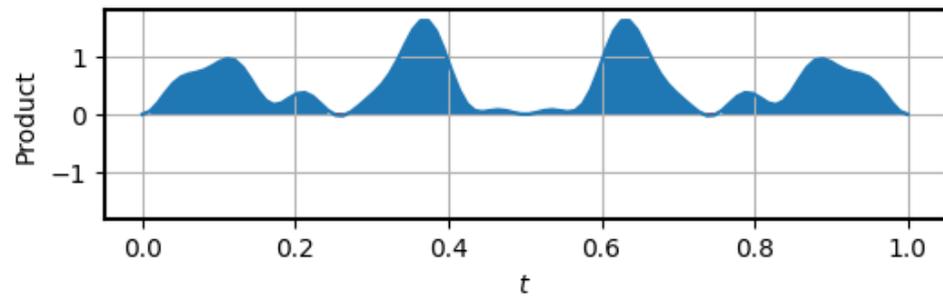
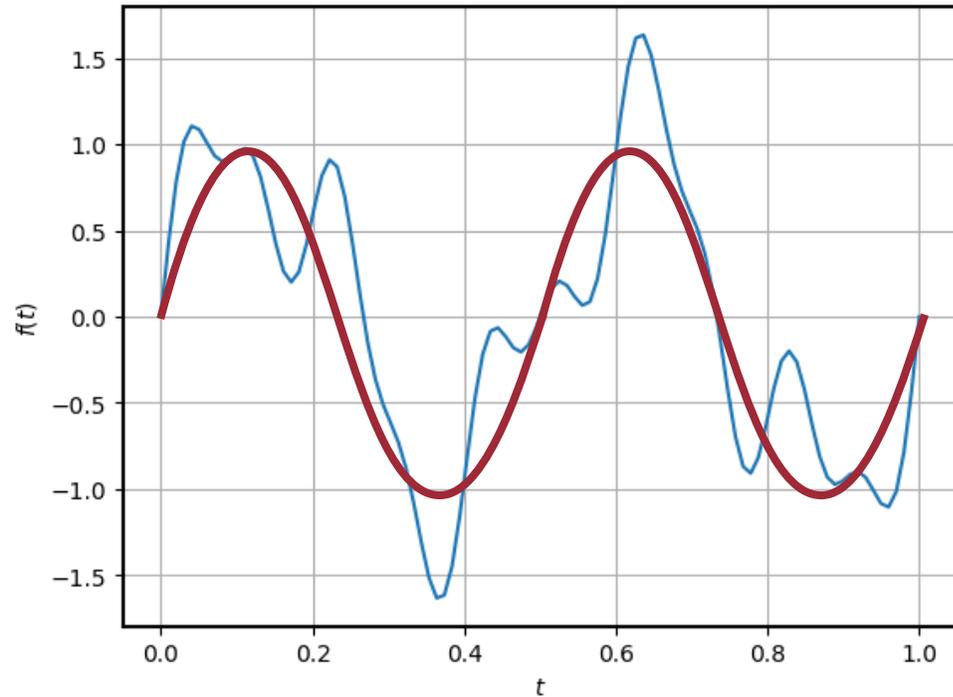
$$e^{-j\theta} = \cos \theta + j \sin \theta$$

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \boxed{\cos(-\omega t)} + j f(t) \boxed{\sin(-\omega t)} dt$$

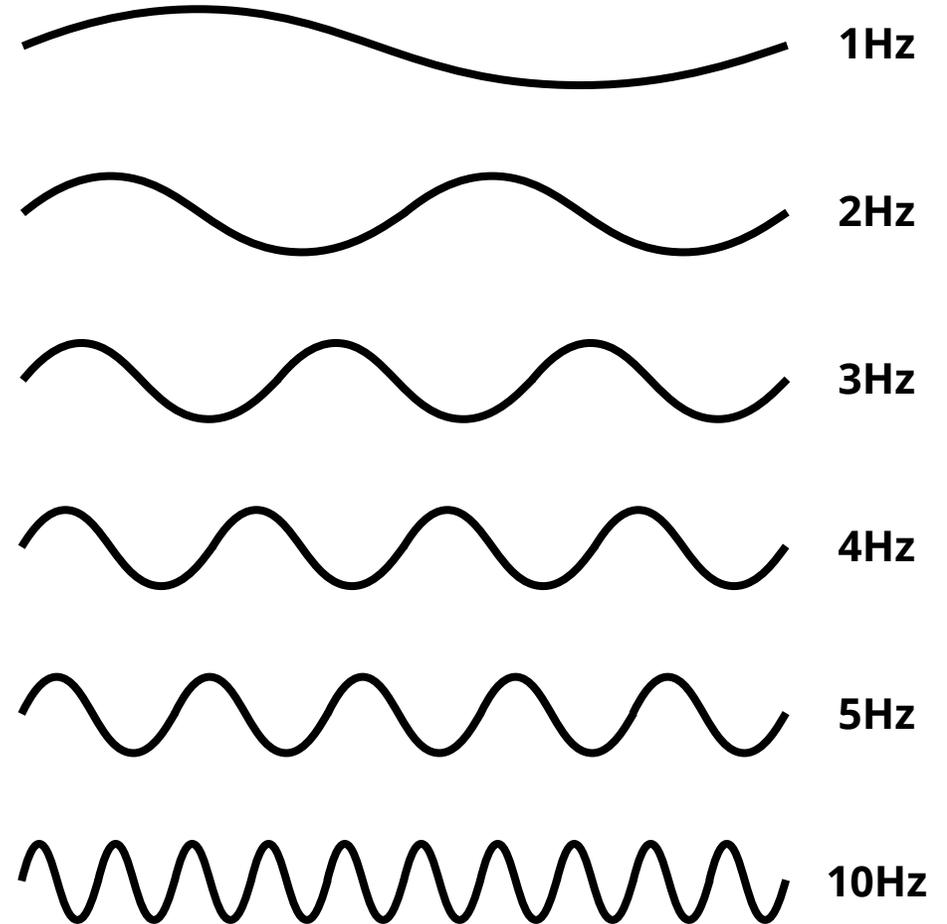
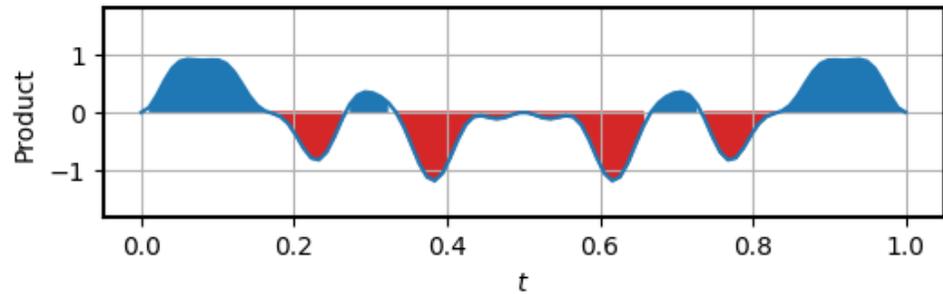
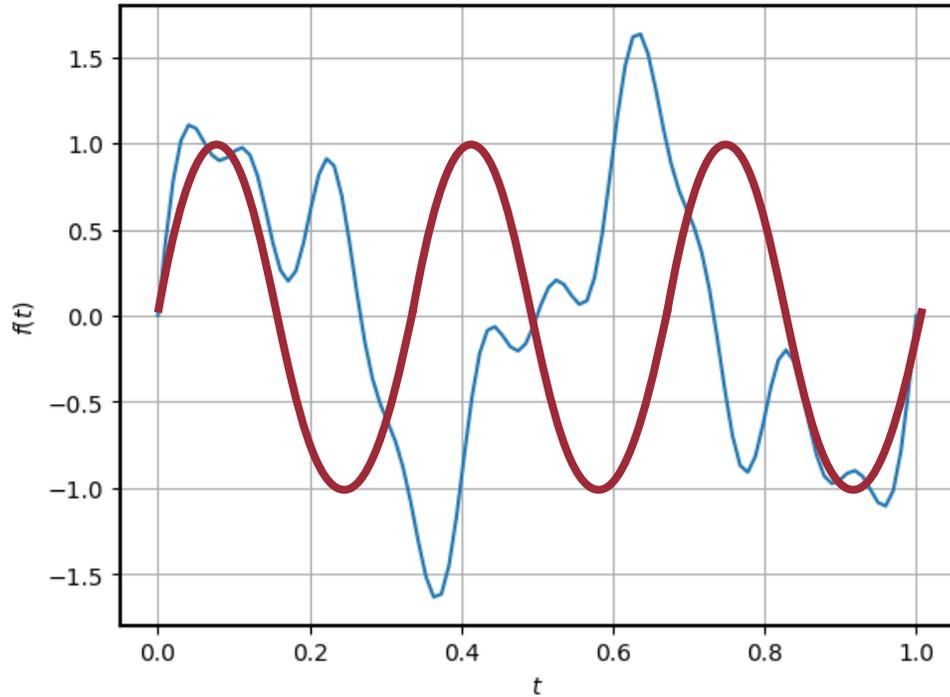
# Demystifying Fourier Transform



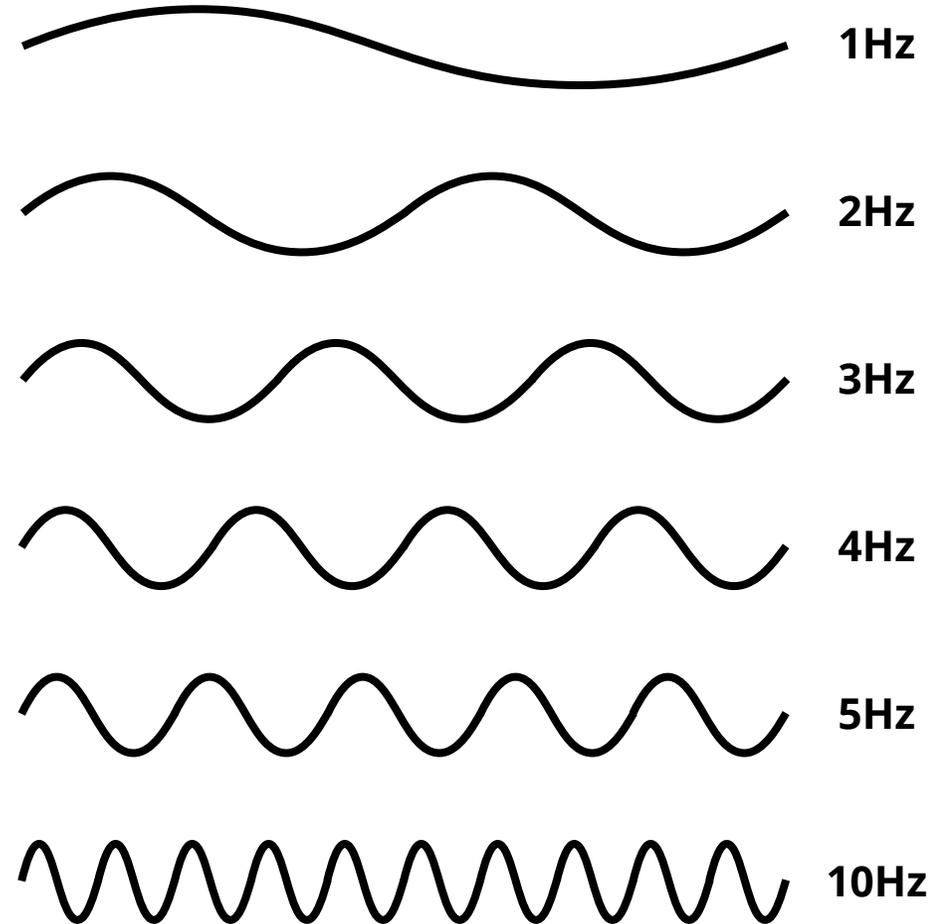
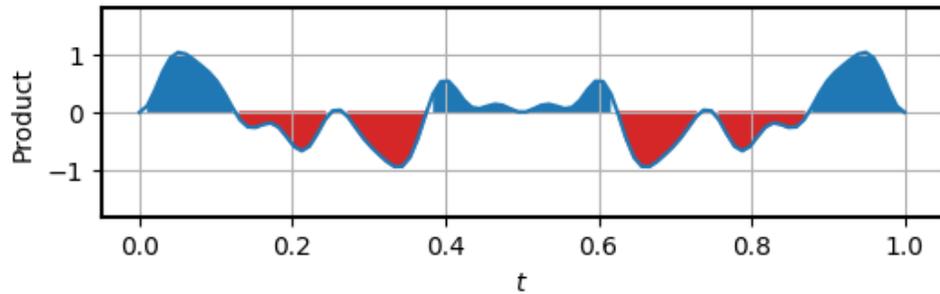
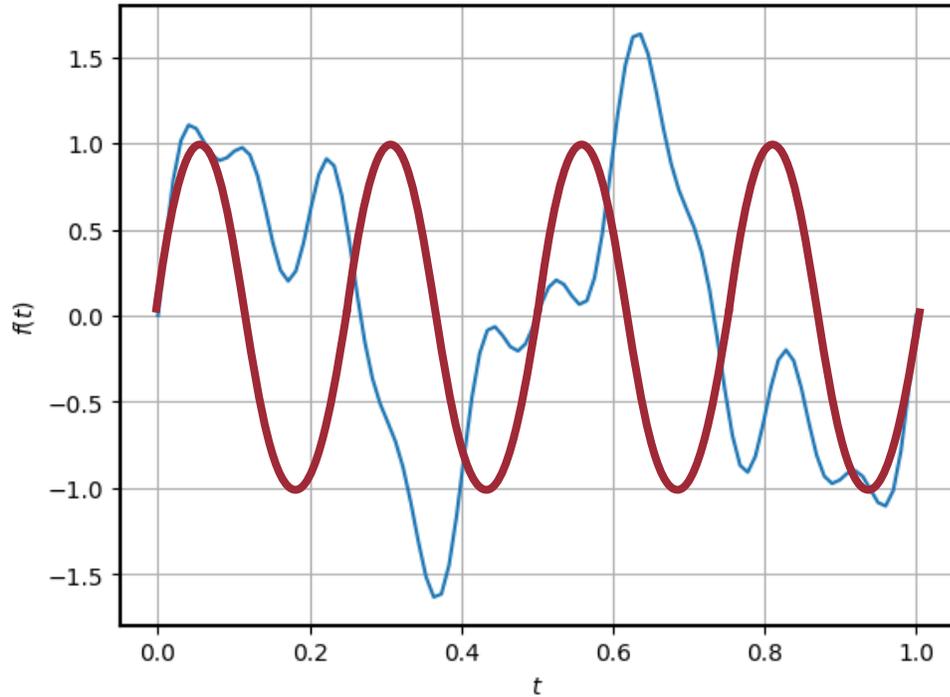
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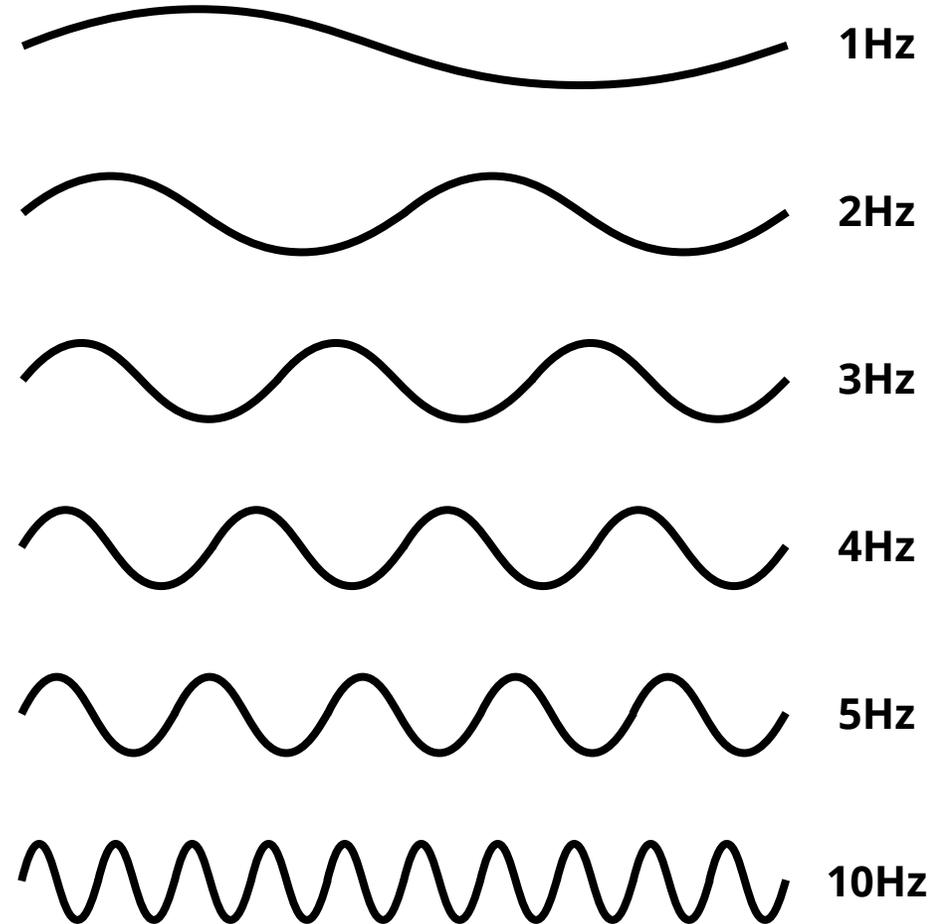
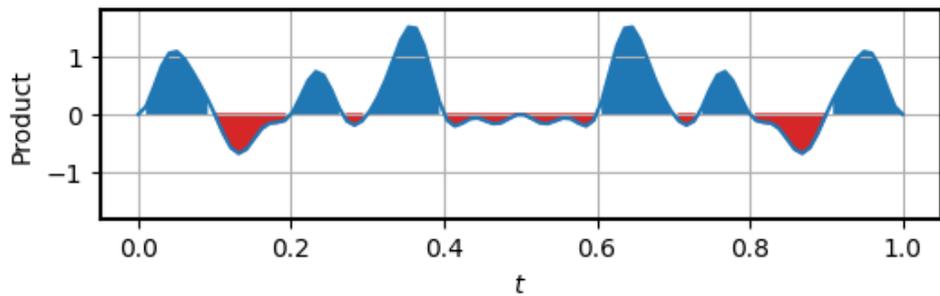
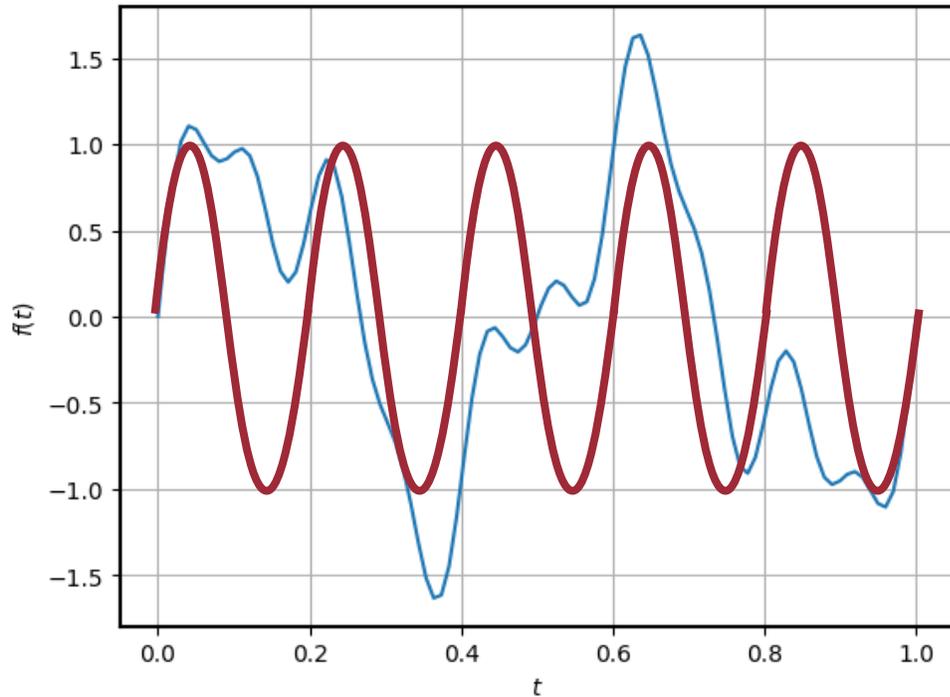
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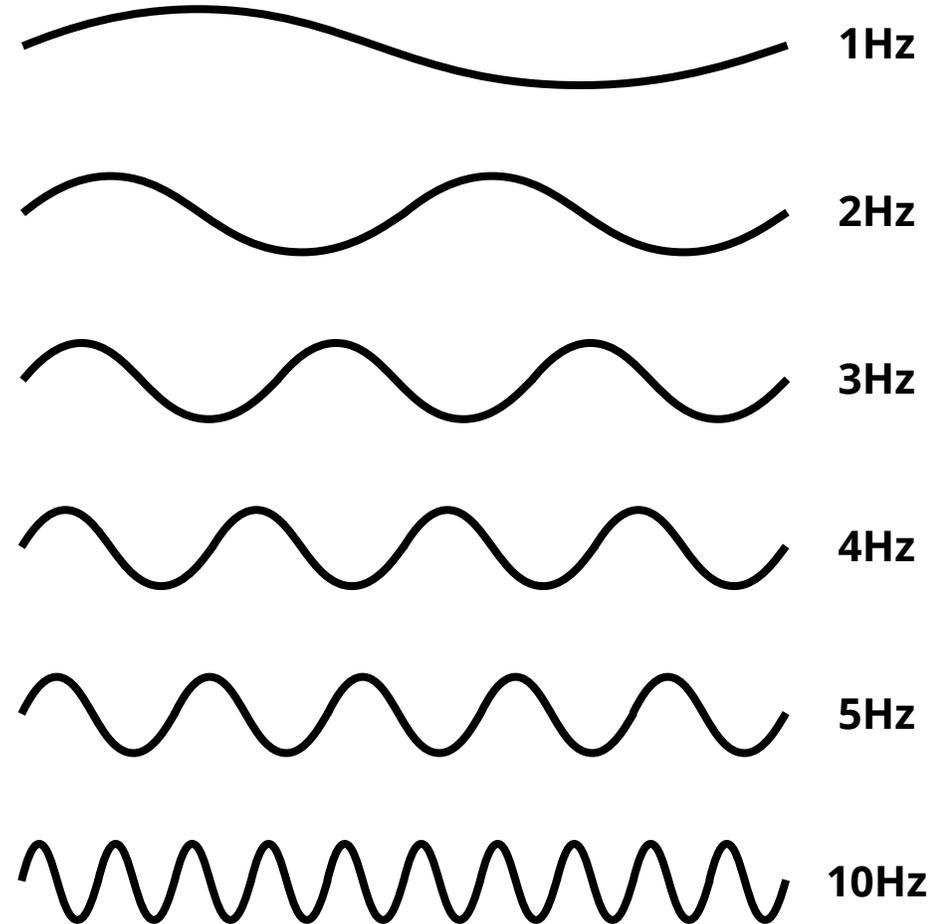
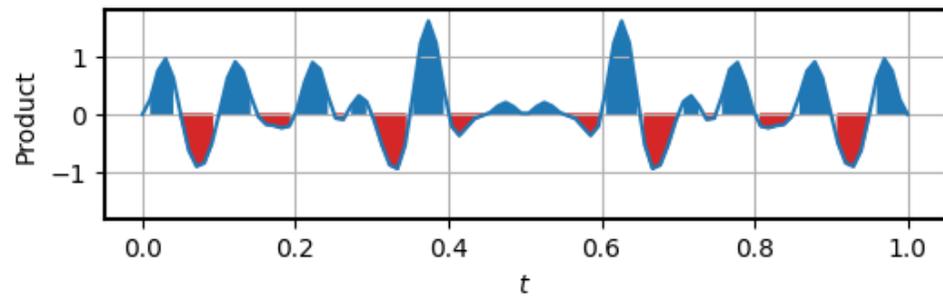
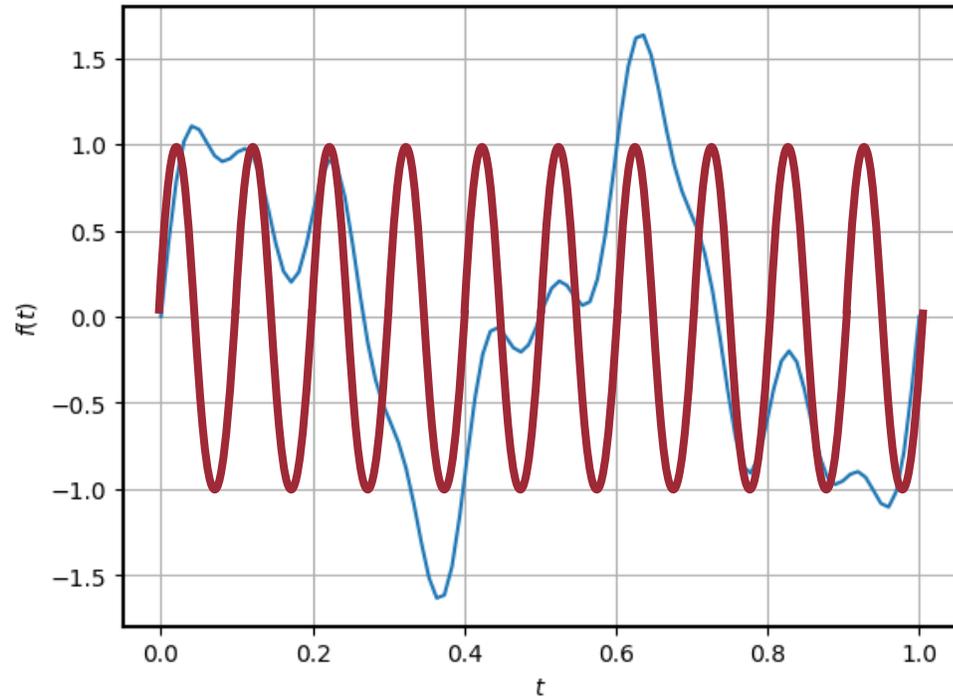
# Demystifying Fourier Transform



# Demystifying Fourier Transform



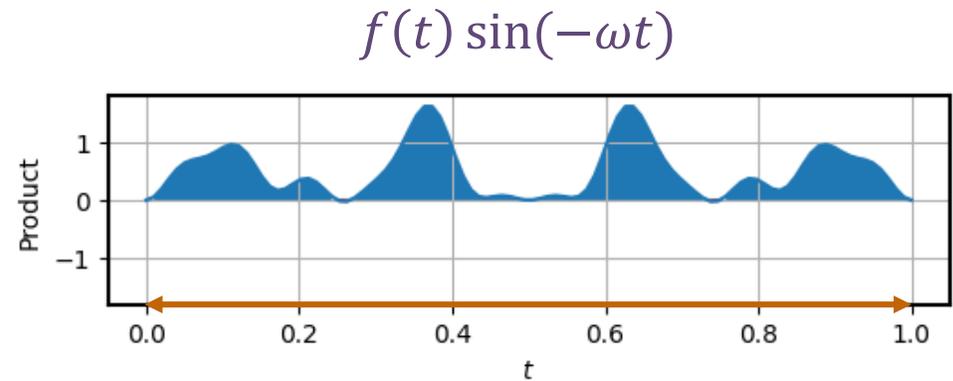
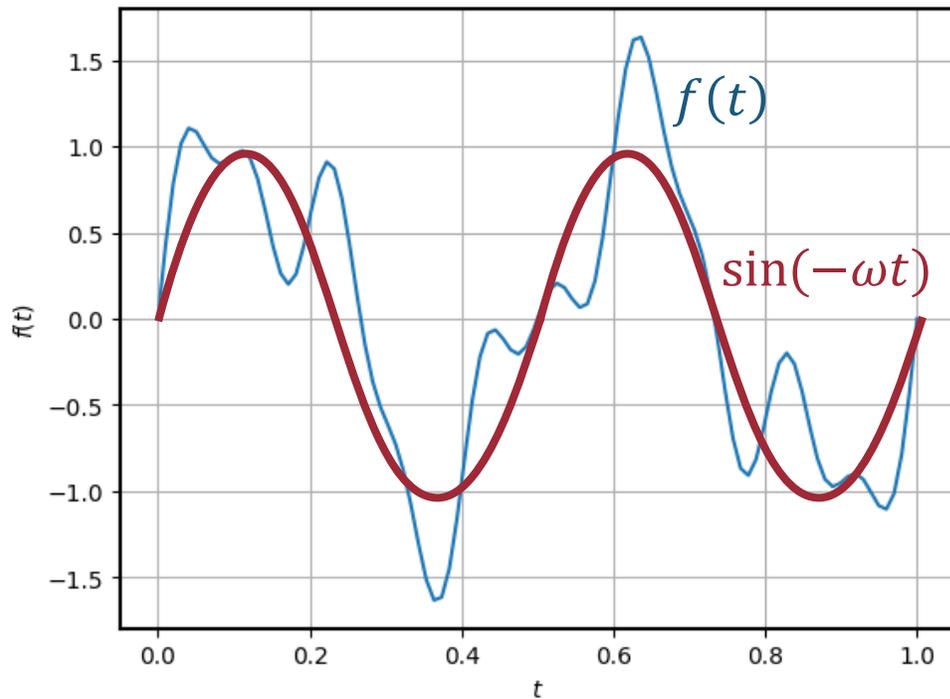
# Demystifying Fourier Transform



# Demystifying Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \cos(-\omega t) + j \int_{-\infty}^{\infty} f(t) \sin(-\omega t) dt$$

Sum over all  $t$

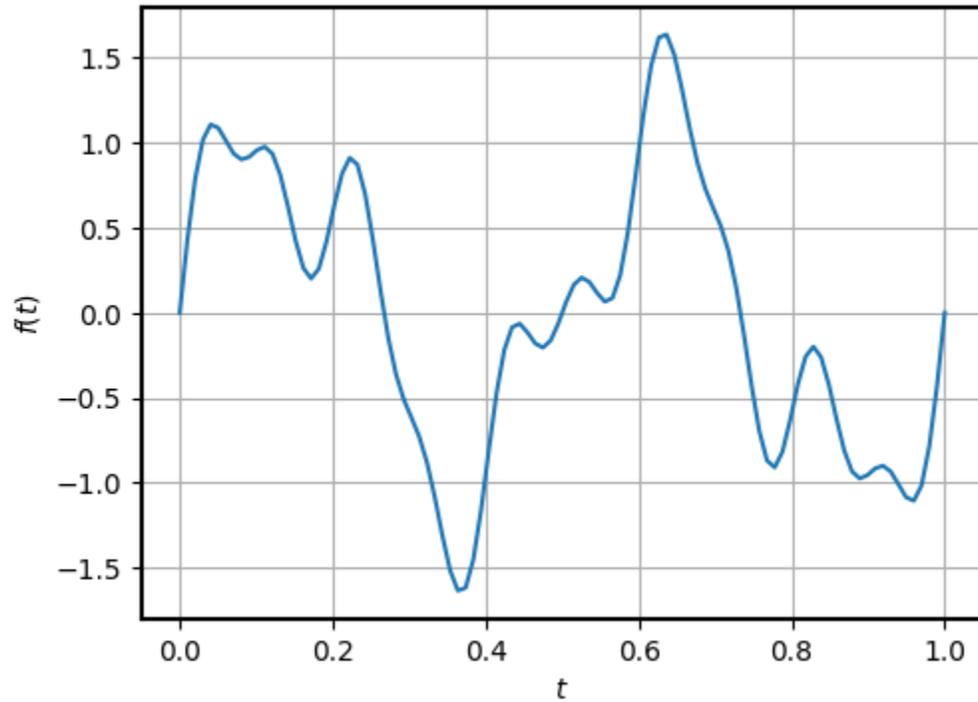


Sum = 0.495

# Demystifying Fourier Transform

## Signal

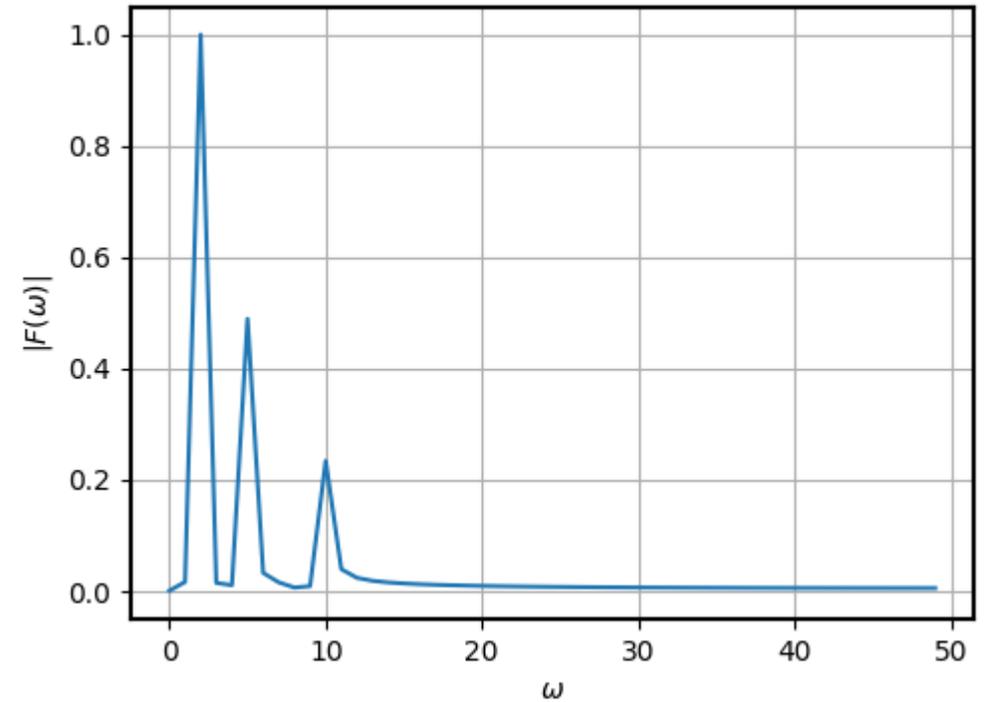
(time-domain)



Fourier Transform  
→

## Spectrum

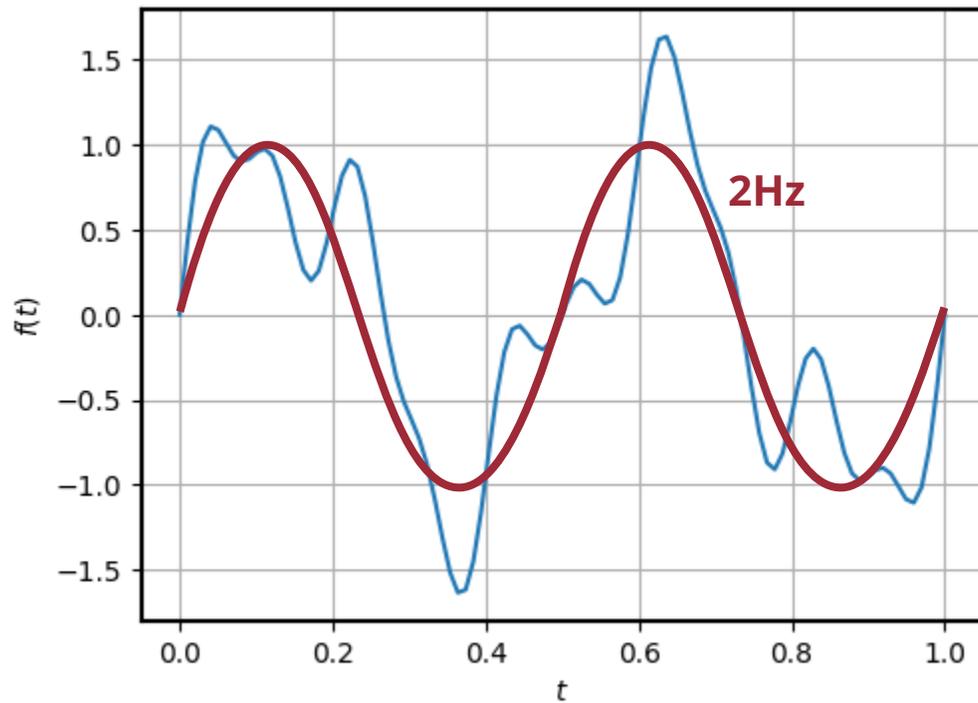
(frequency-domain)



# Demystifying Fourier Transform

## Signal

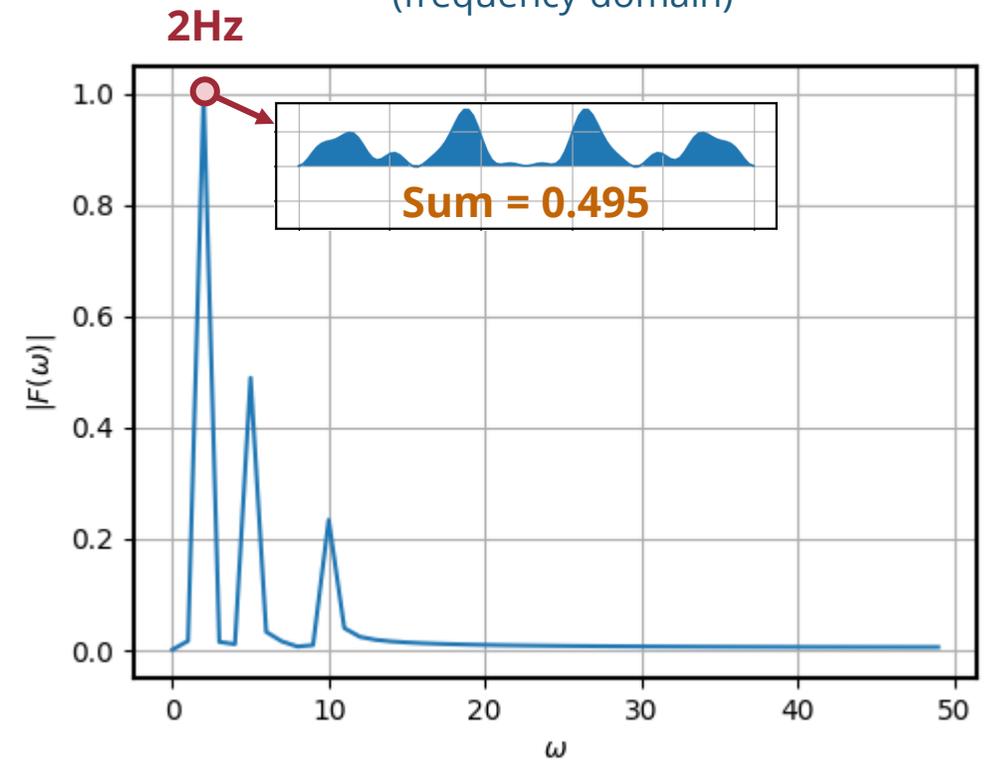
(time-domain)



Fourier Transform  
→

## Spectrum

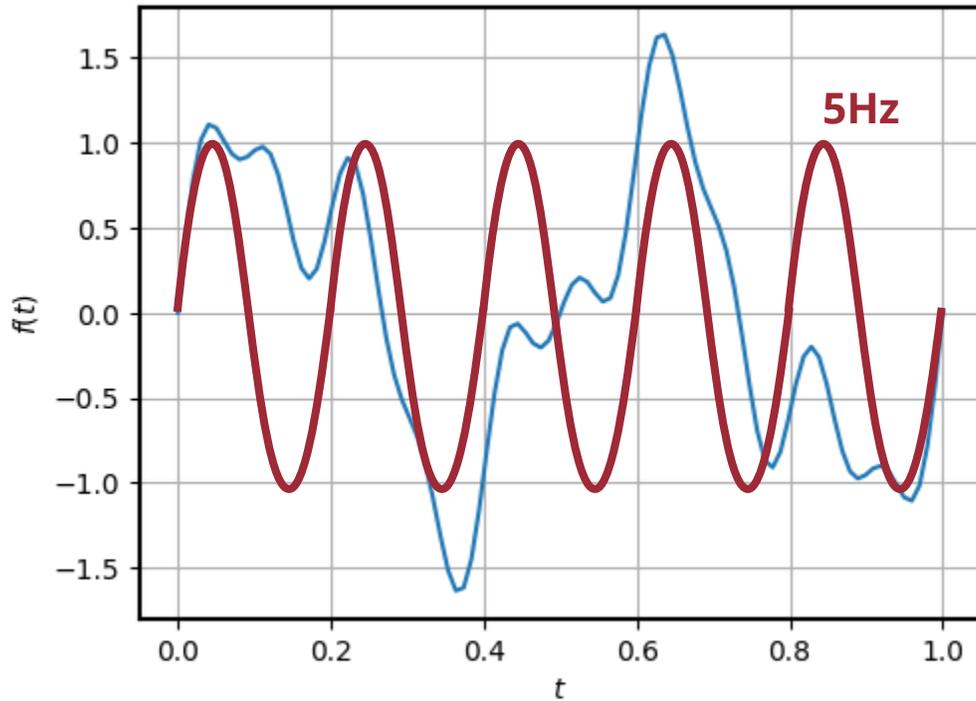
(frequency-domain)



# Demystifying Fourier Transform

## Signal

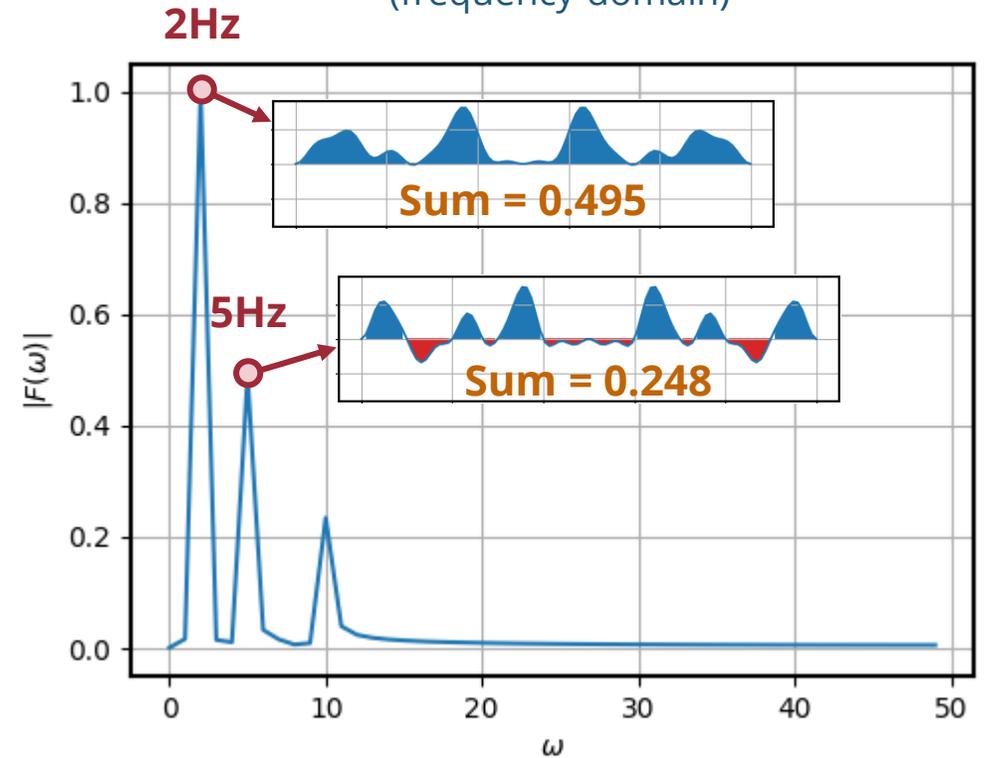
(time-domain)



Fourier Transform  
→

## Spectrum

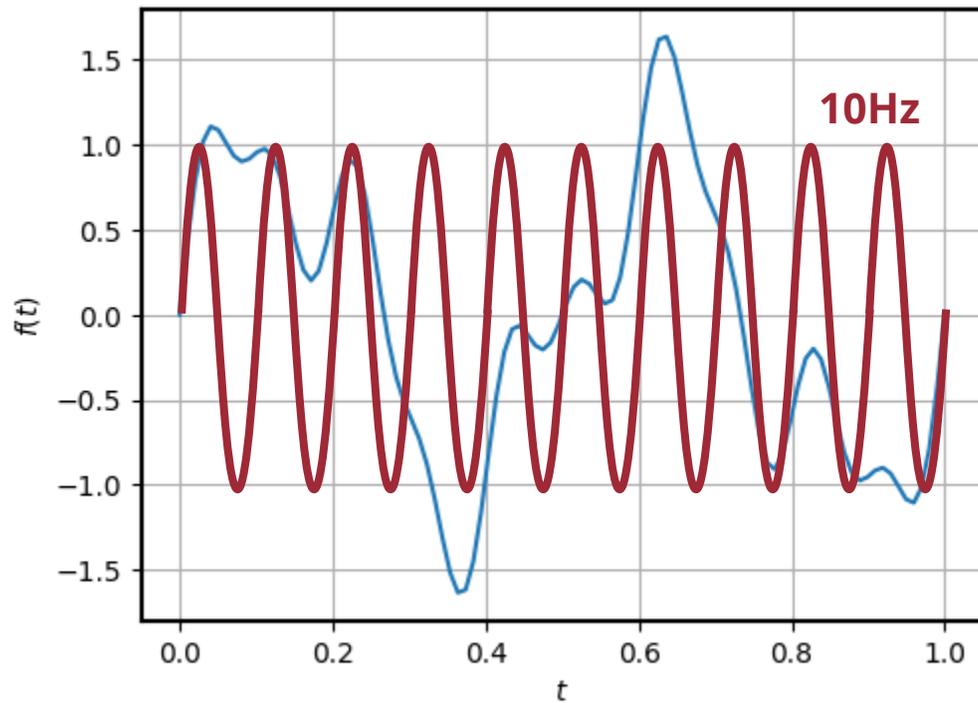
(frequency-domain)



# Demystifying Fourier Transform

## Signal

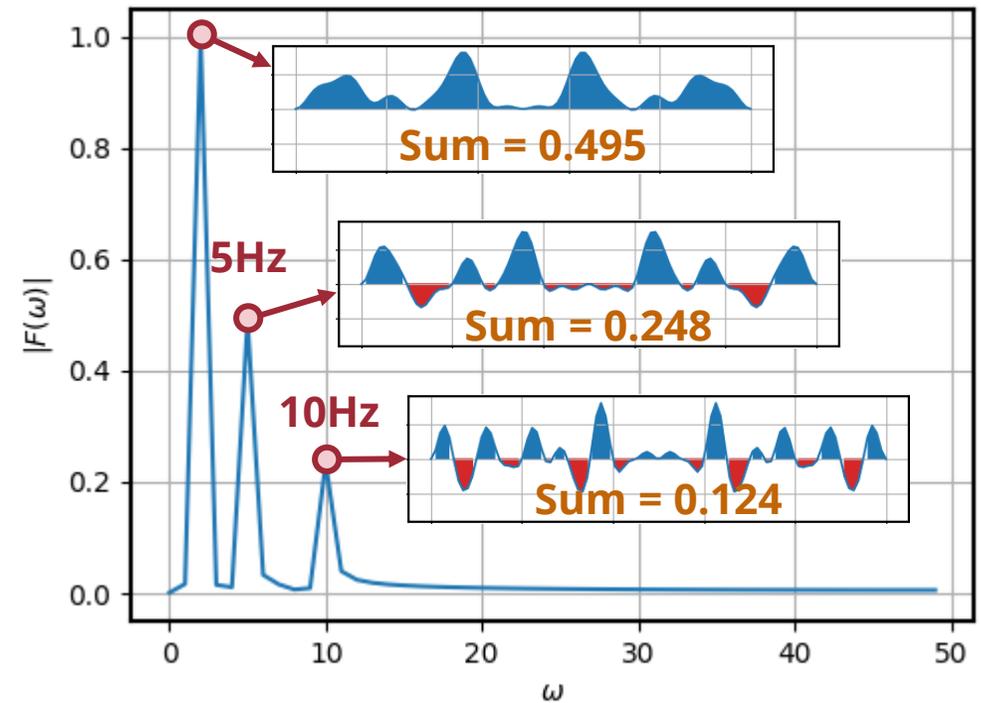
(time-domain)



Fourier Transform  
→

## Spectrum

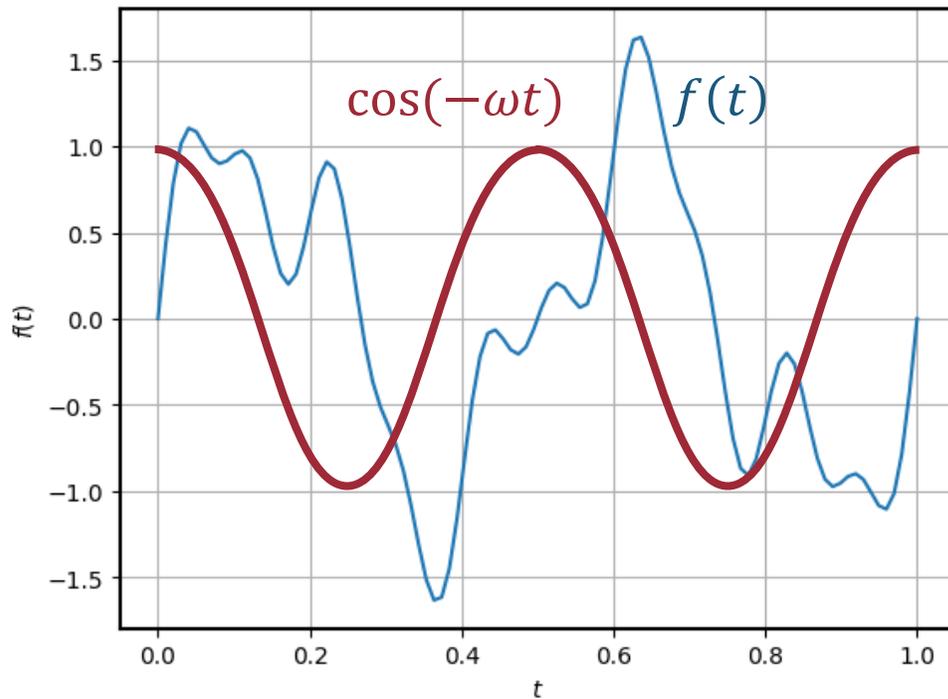
(frequency-domain)



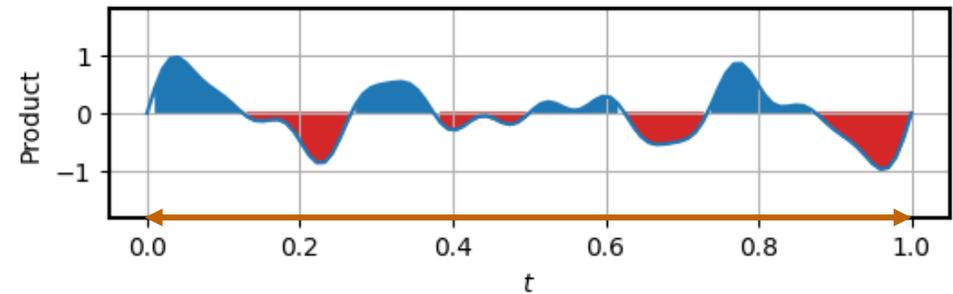
# Demystifying Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \cos(-\omega t) + j f(t) \sin(-\omega t) dt$$

Sum over all  $t$

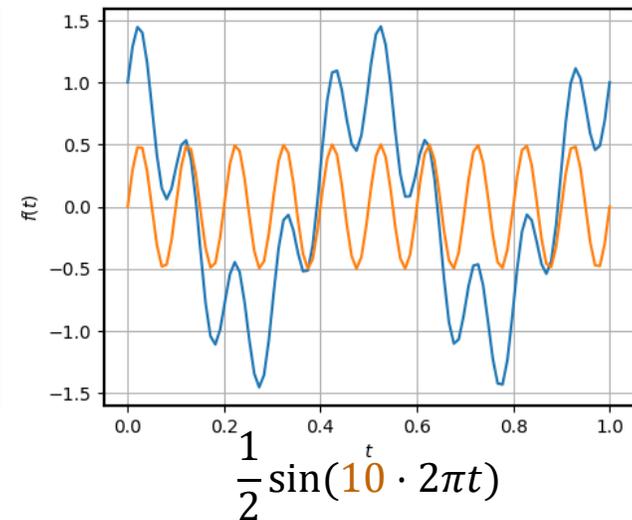
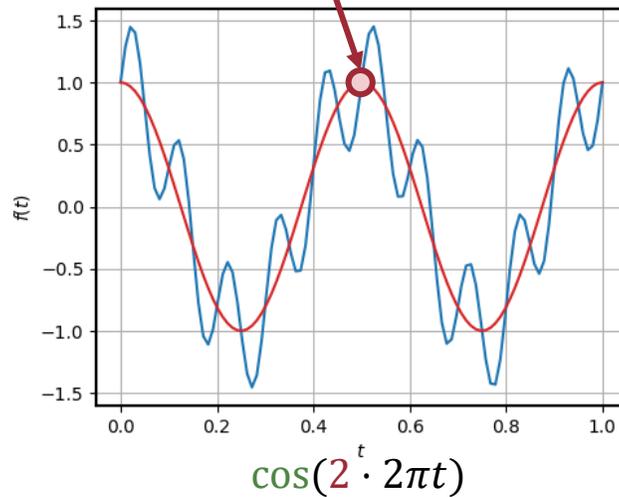
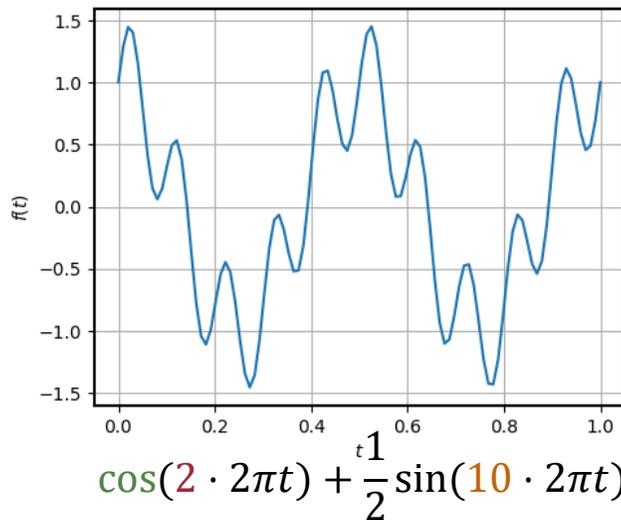
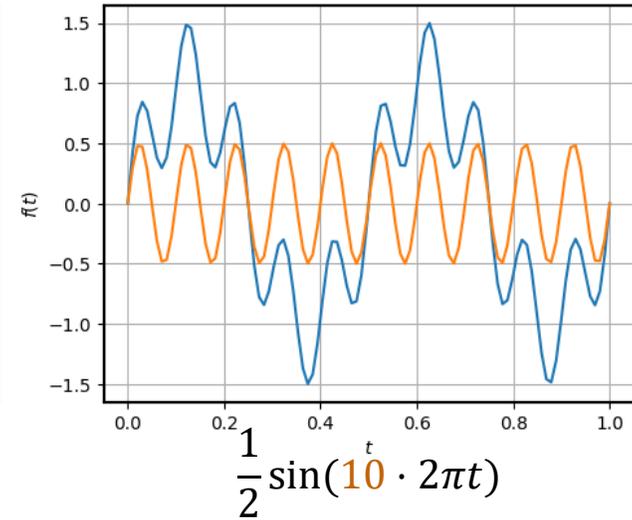
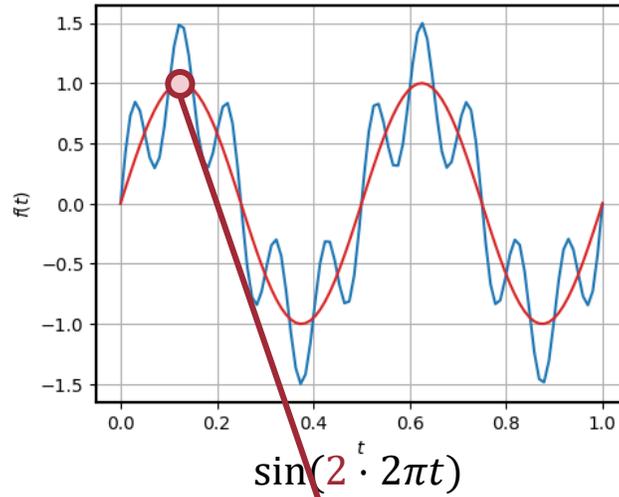
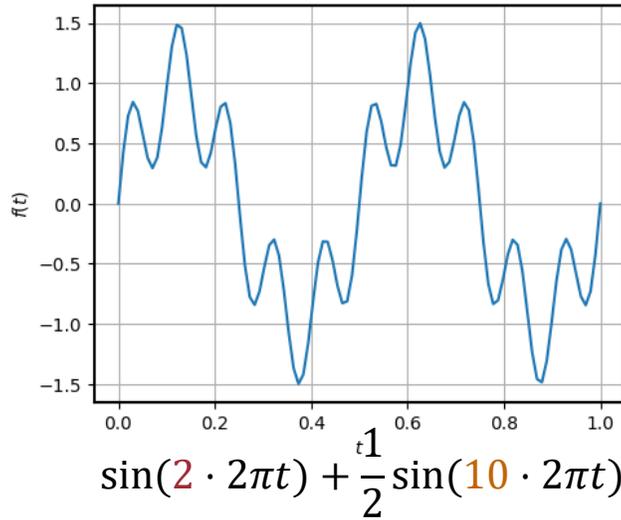


$f(t) \cos(-\omega t)$



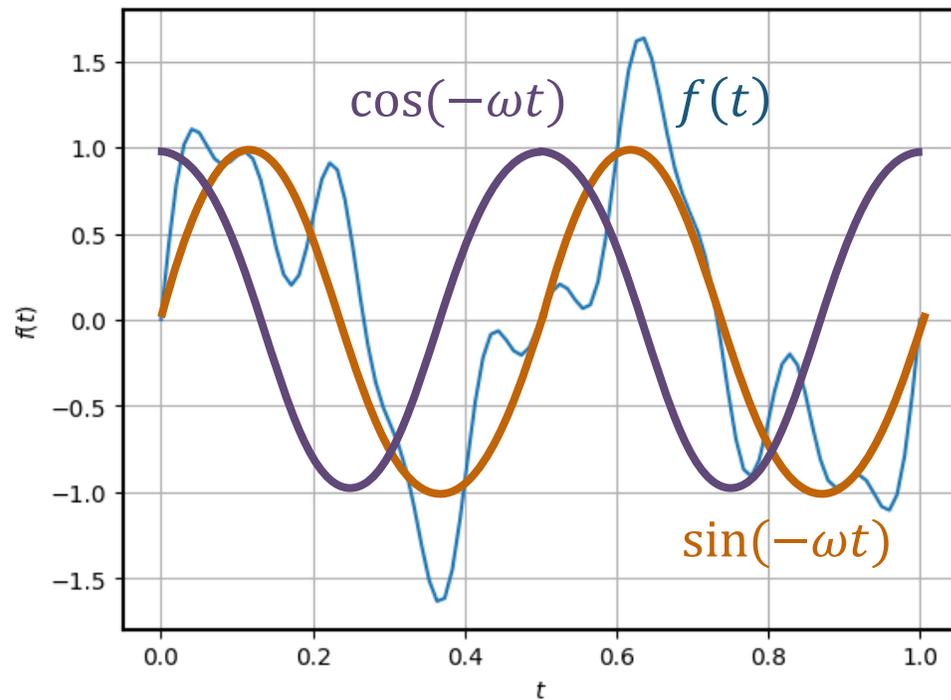
Sum = 0

# Phase



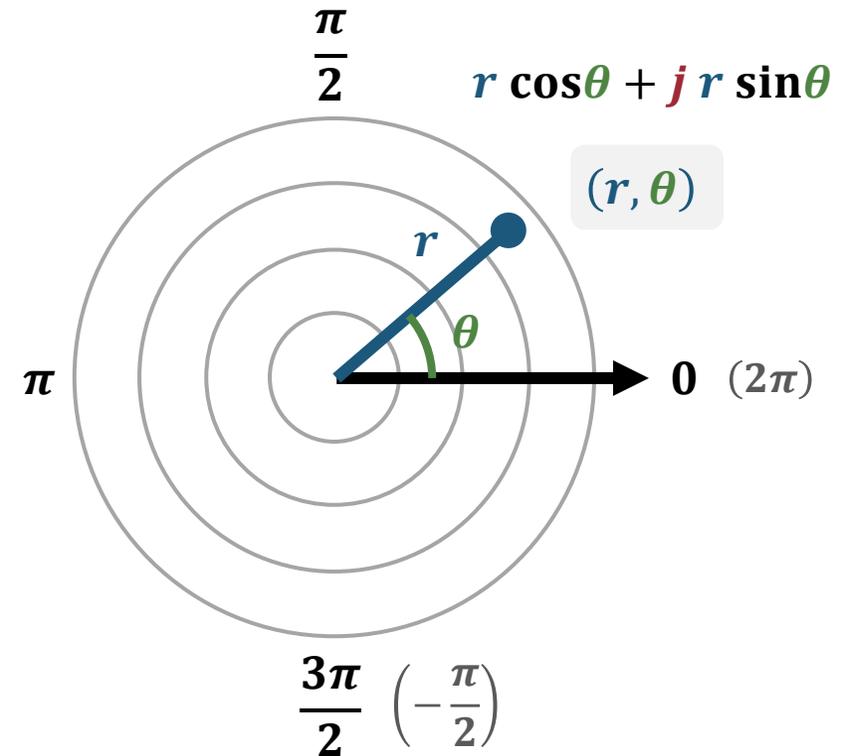
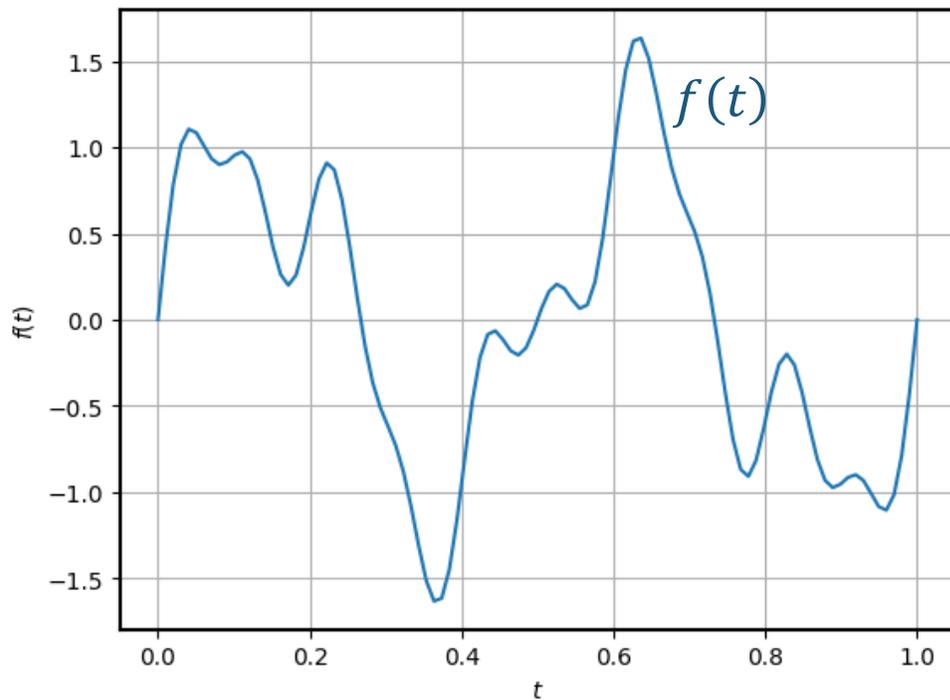
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$$F(\omega) = \int_{-\infty}^{\infty} \underbrace{f(t) \cos(-\omega t)}_{\text{Real part}} + \underbrace{j f(t) \sin(-\omega t)}_{\text{Imaginary part}} dt$$



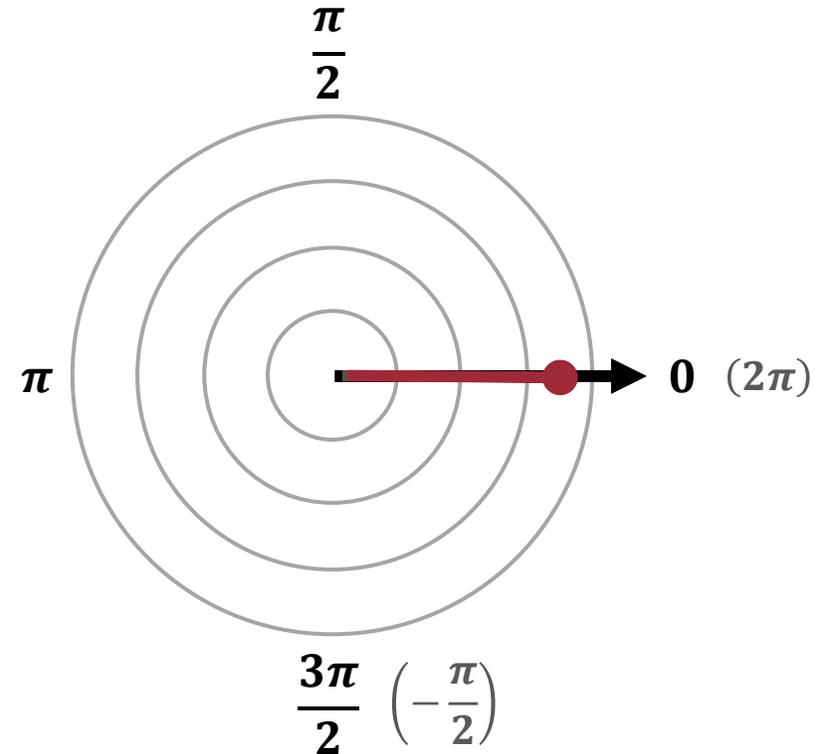
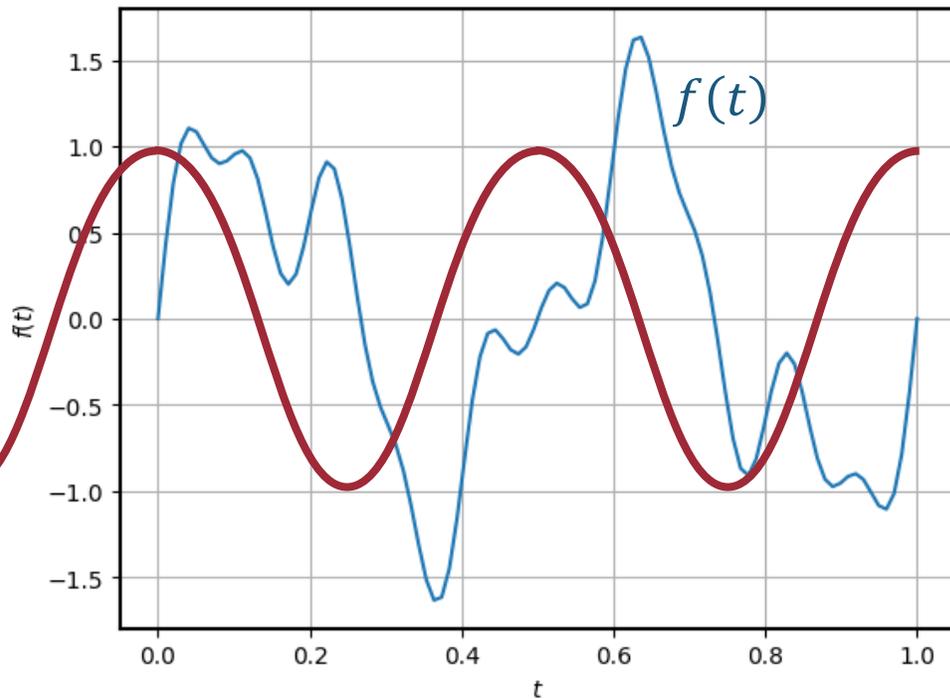
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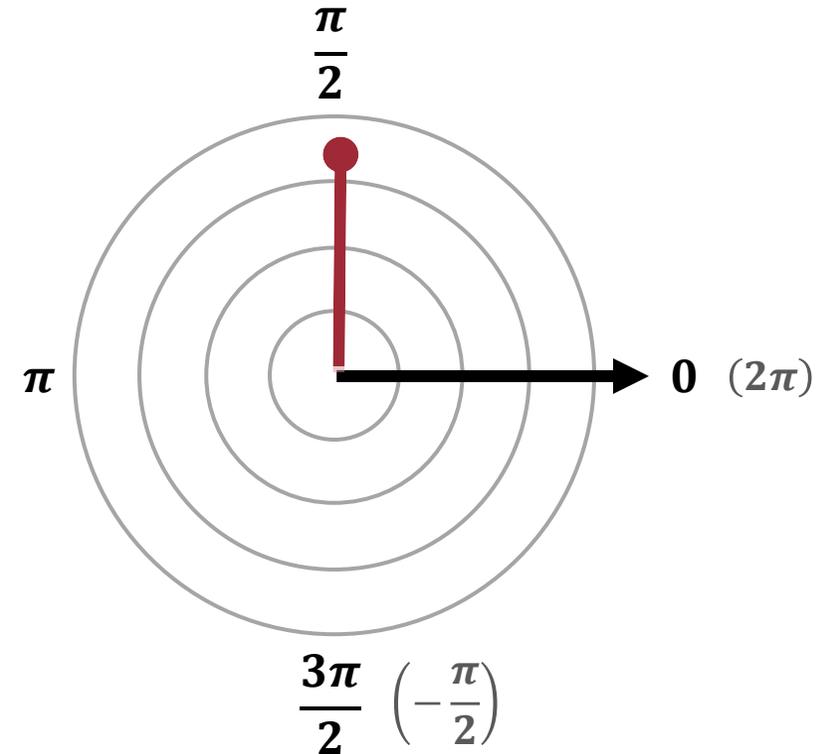
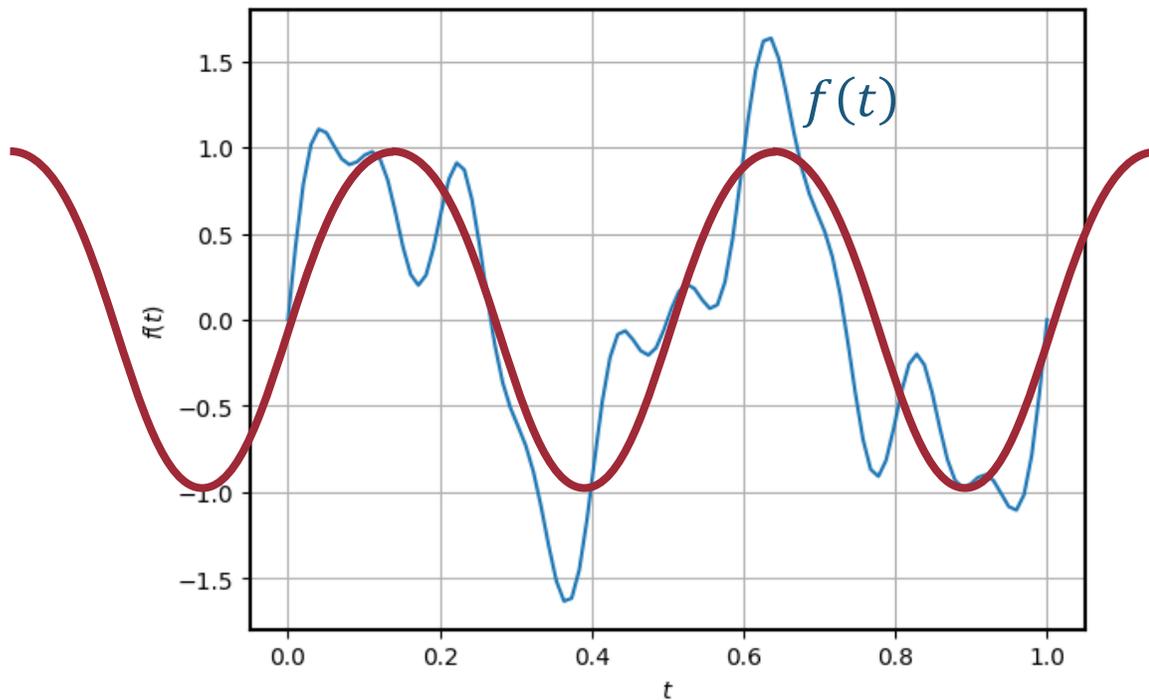
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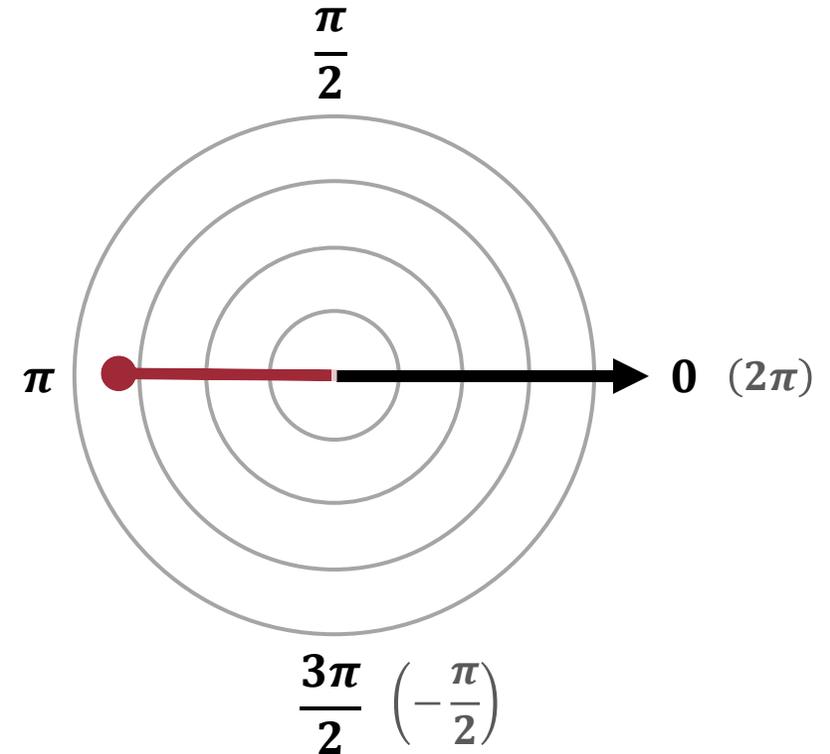
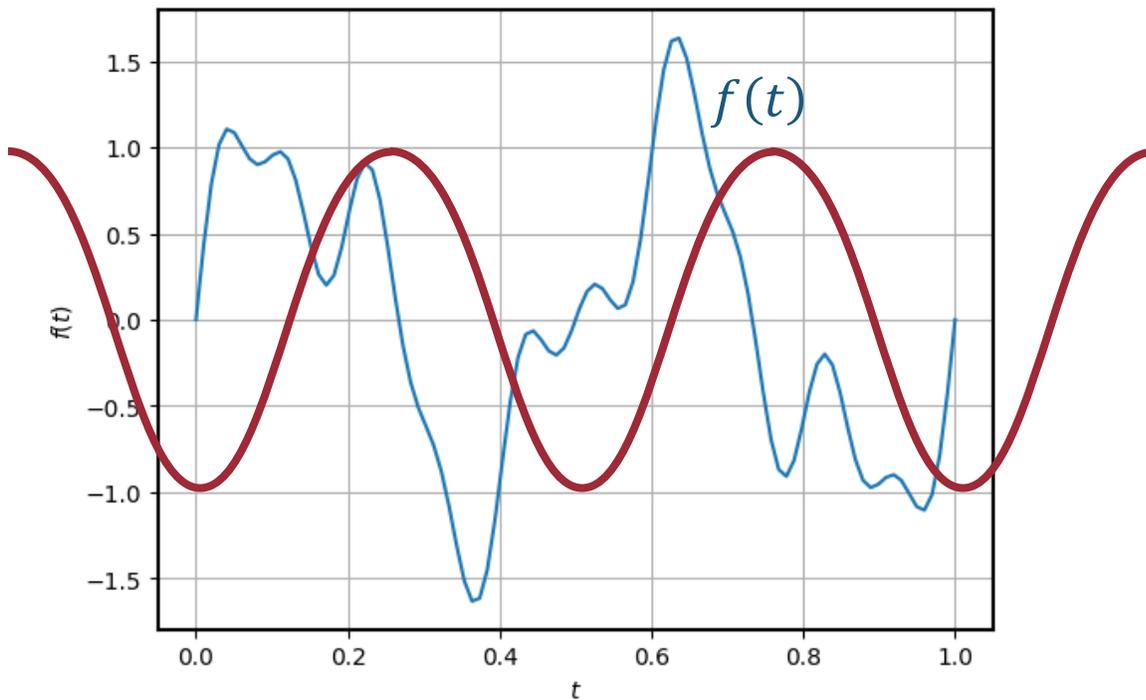
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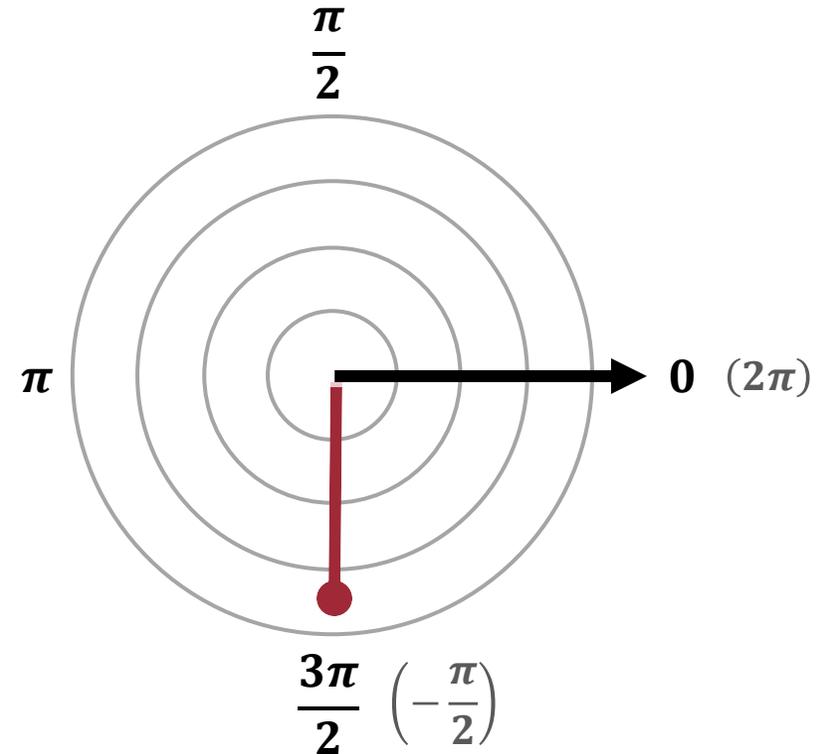
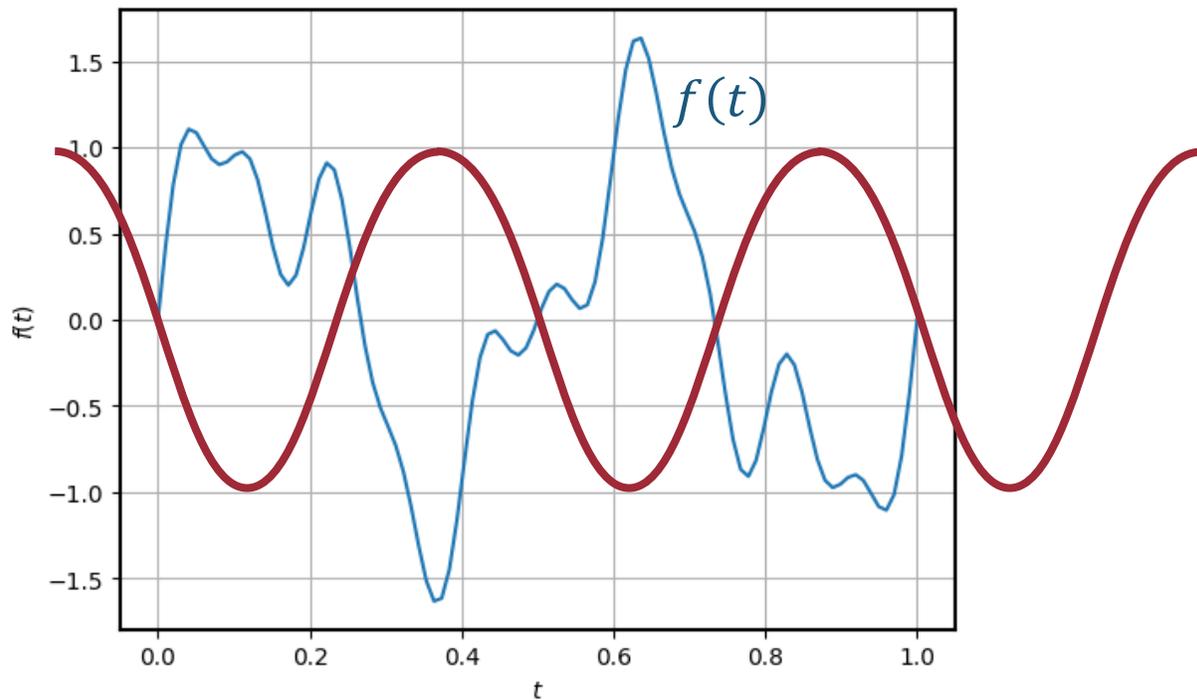
# Demystifying Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} \underbrace{f(t) \cos(-\omega t)}_{\text{Real part}} + \underbrace{j f(t) \sin(-\omega t)}_{\text{Imaginary part}} dt$$

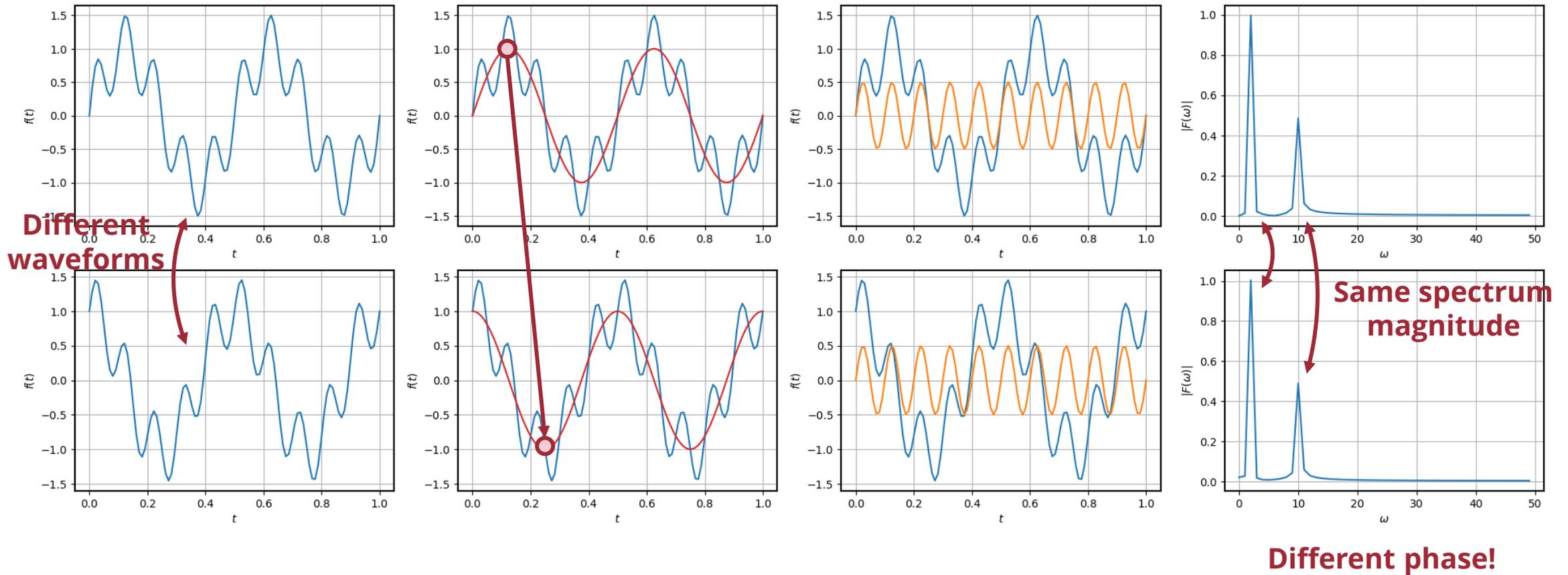


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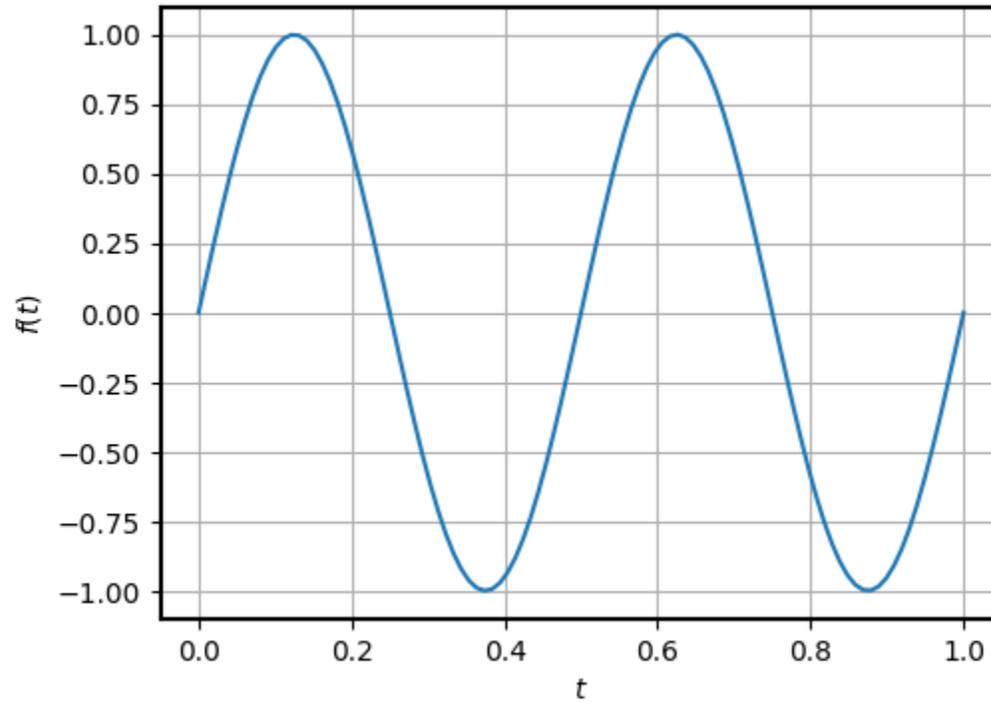
# Magnitude & Phase



# Example: A 2Hz Sine Wave

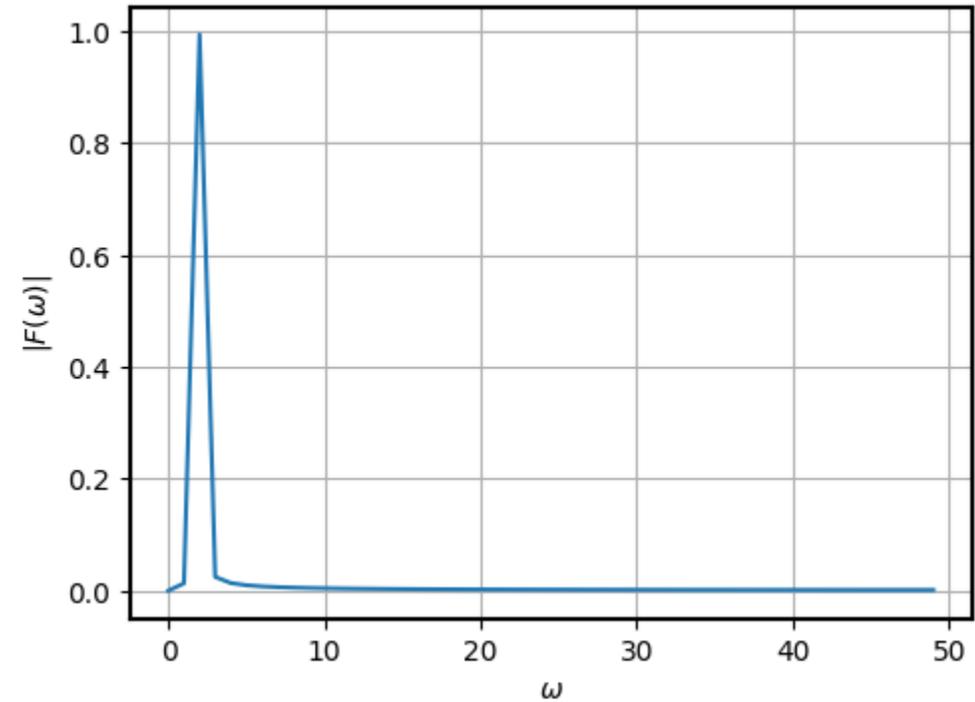
**Signal**

(time-domain)



**Spectrum**

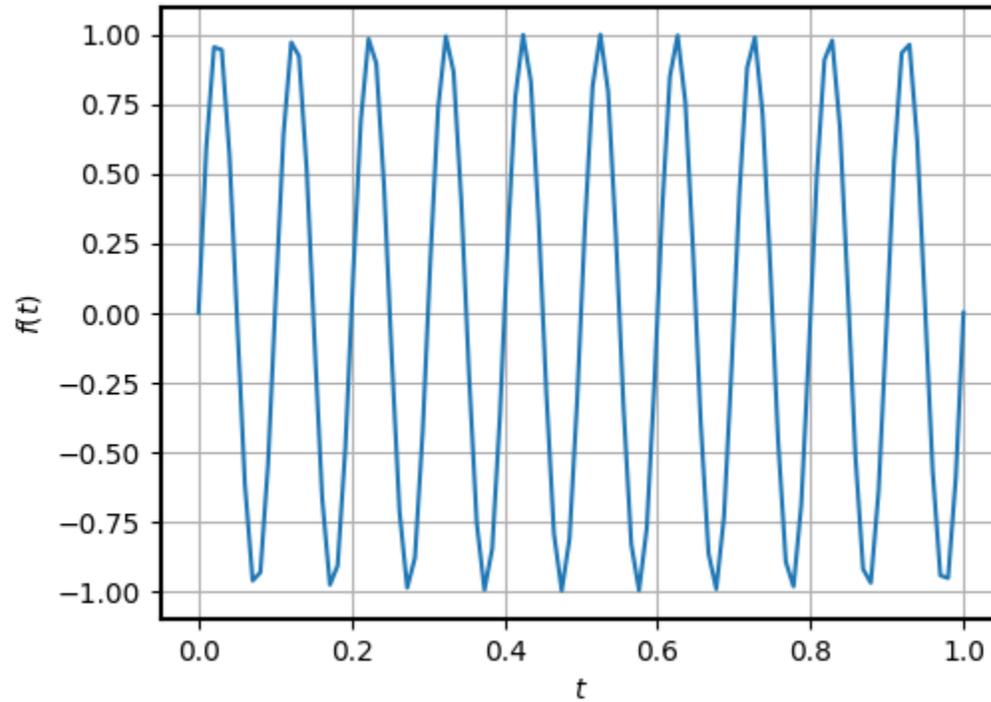
(frequency-domain)



# Example : A 10Hz Sine Wave

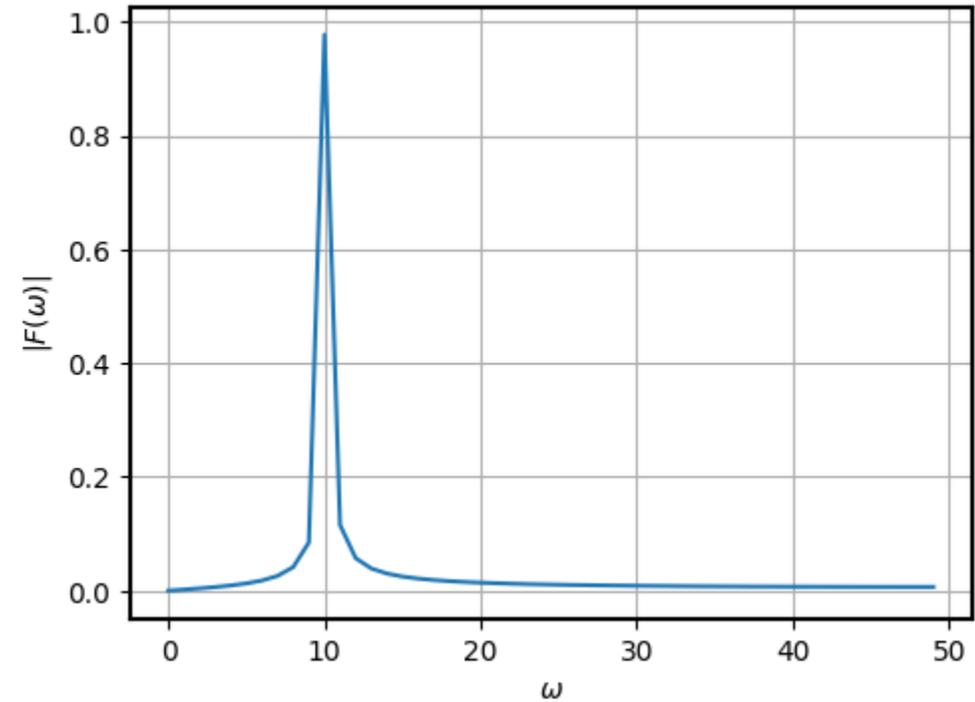
**Signal**

(time-domain)



**Spectrum**

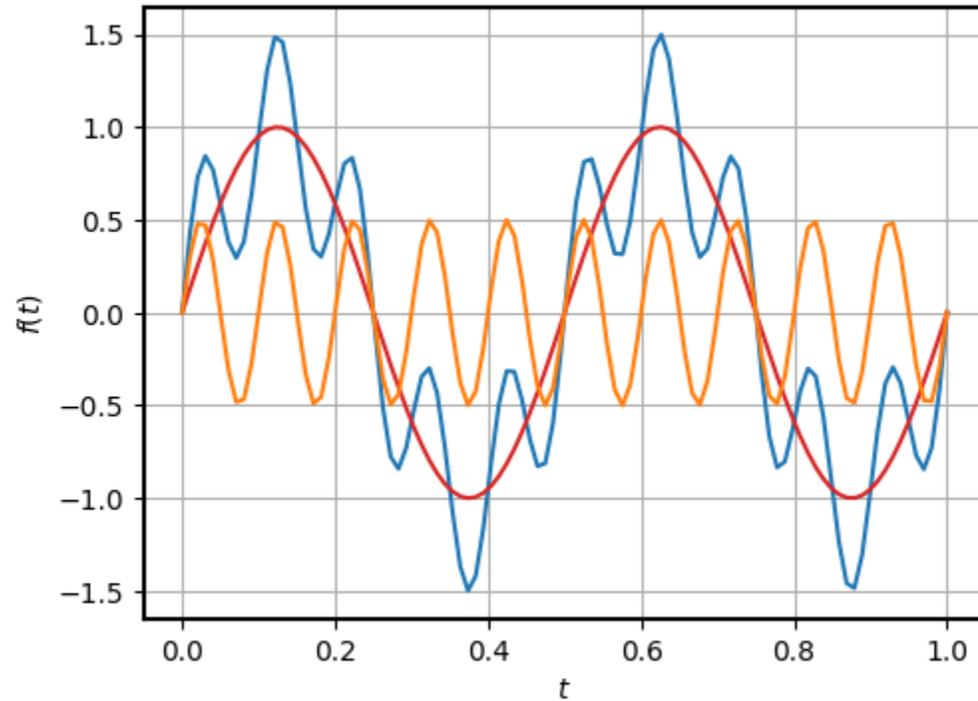
(frequency-domain)



# Example: Sum of a 10Hz & 2Hz Sine Waves

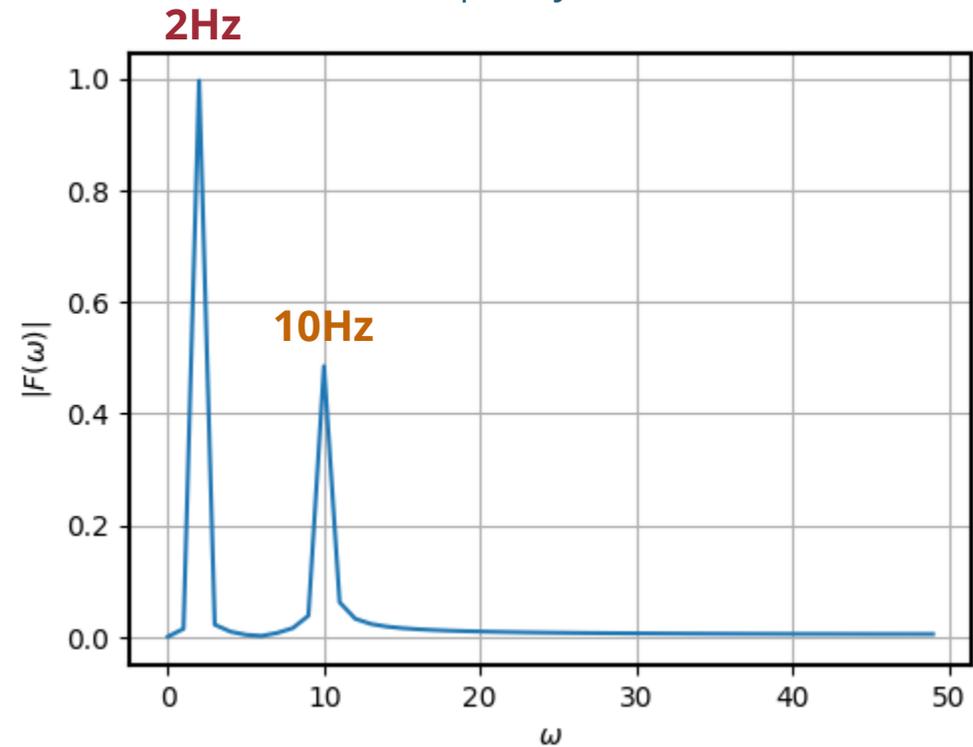
**Signal**

(time-domain)



**Spectrum**

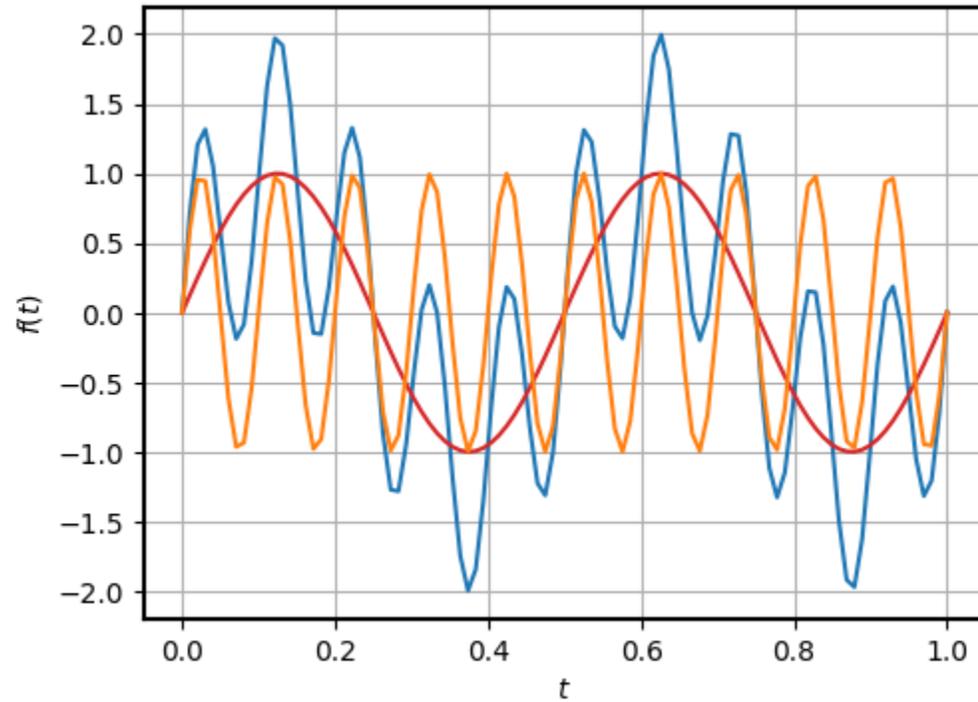
(frequency-domain)



# How about this?

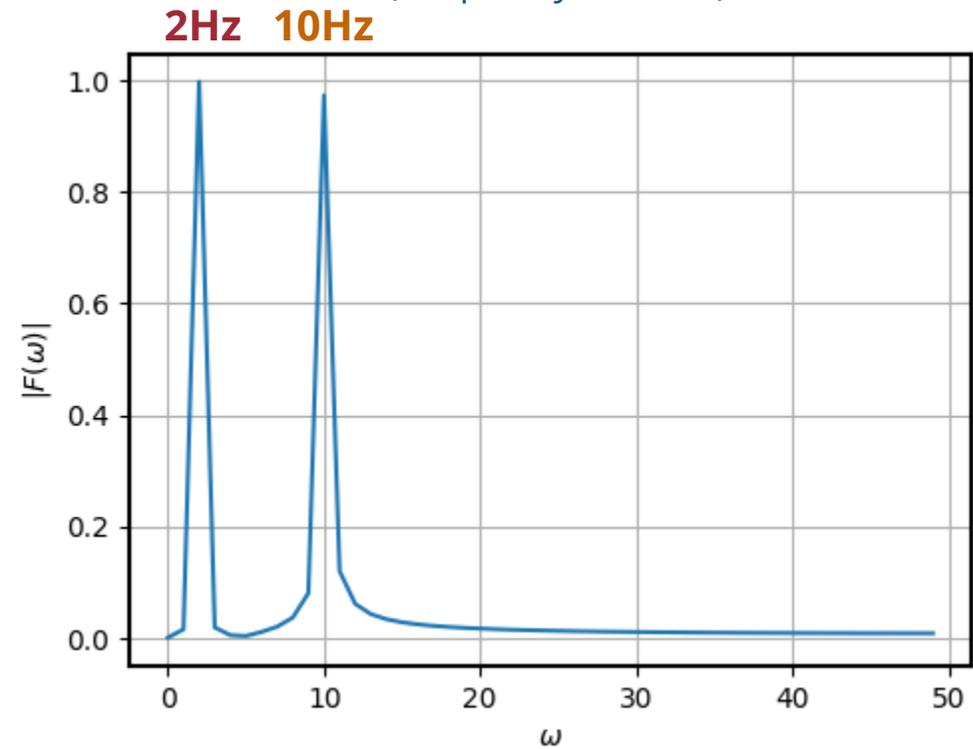
**Signal**

(time-domain)



**Spectrum**

(frequency-domain)



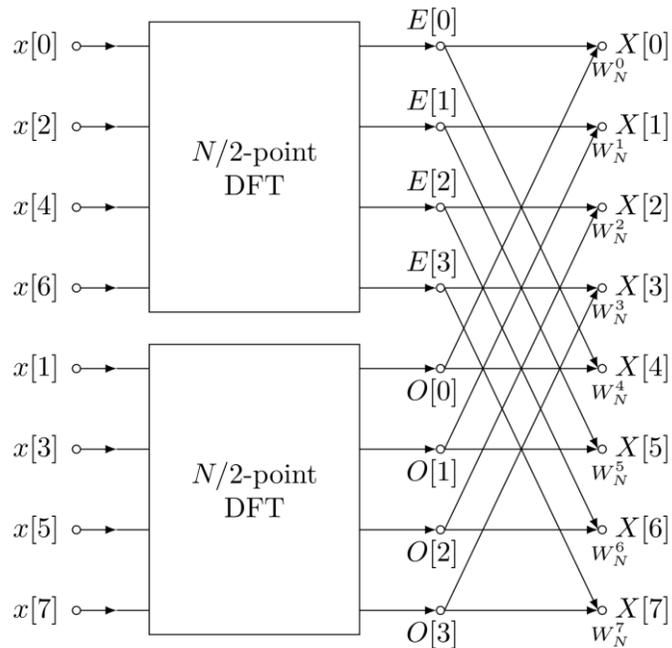
# Discrete Fourier Transform (DFT)

- **Intuition:** Fourier transform with **discrete time and frequency**
  - Used for **digital audio** → we cannot achieve an infinite sampling rate...
- Mathematical formulation:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j2\pi\frac{k}{N}n}$$

# In Practice: Fast Fourier Transform (FFT)

- An efficient implementation of discrete Fourier transform
  - Reduce the complexity from  $O(n^2)$  to  $O(n \log n)$



(Source: Yangwenbo99 via Wikimedia)

Top 10 algorithms from the 20<sup>th</sup> century

**Computing**  
in **SCIENCE & ENGINEERING**



IEEE

IEEE  
COMPUTER  
SOCIETY  
www.computer.org/cta

# Time-Frequency Analysis

# Fourier Transform of a Trumpet Sound

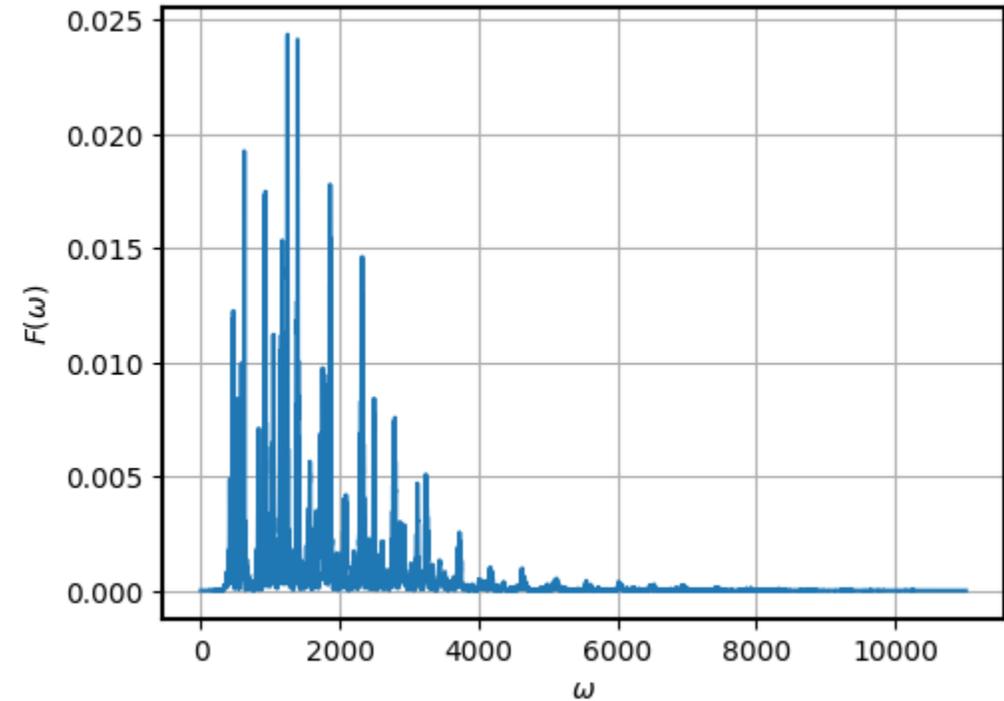
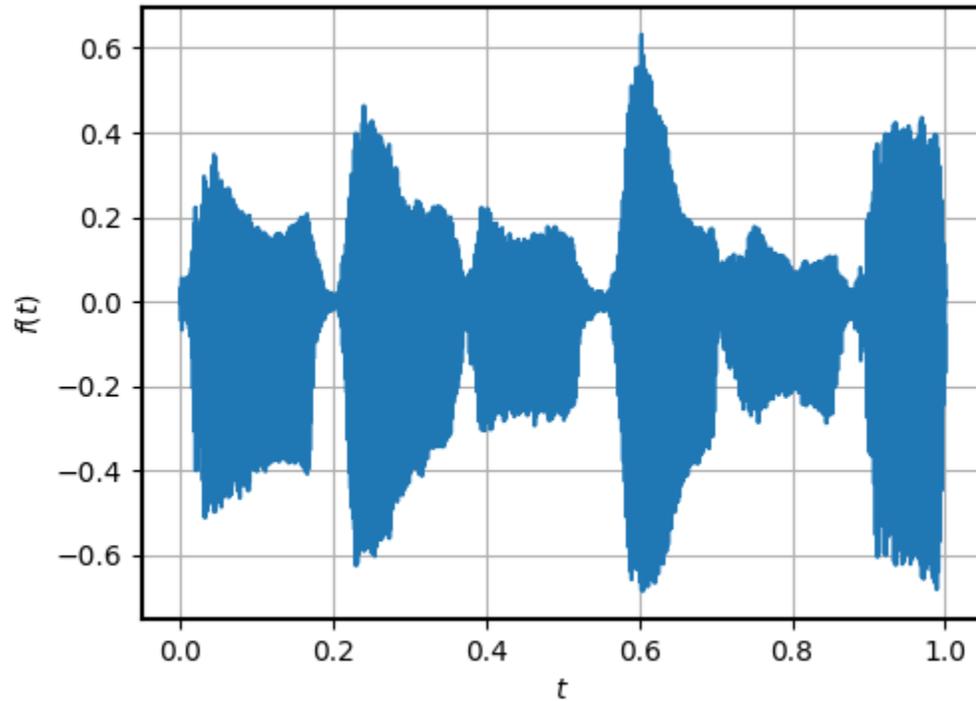
Signal

(time-domain)



Spectrum

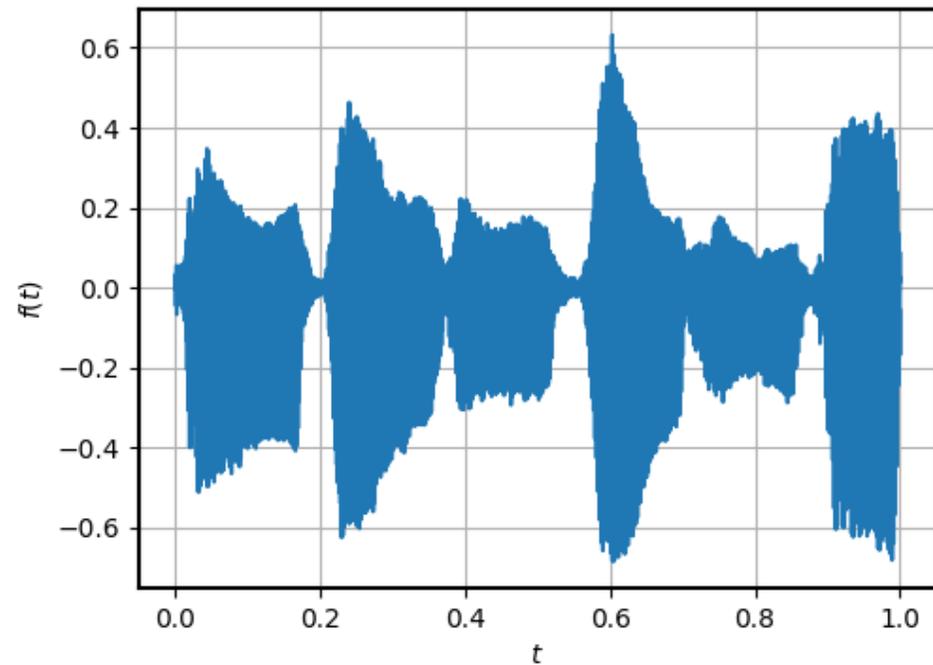
(frequency-domain)



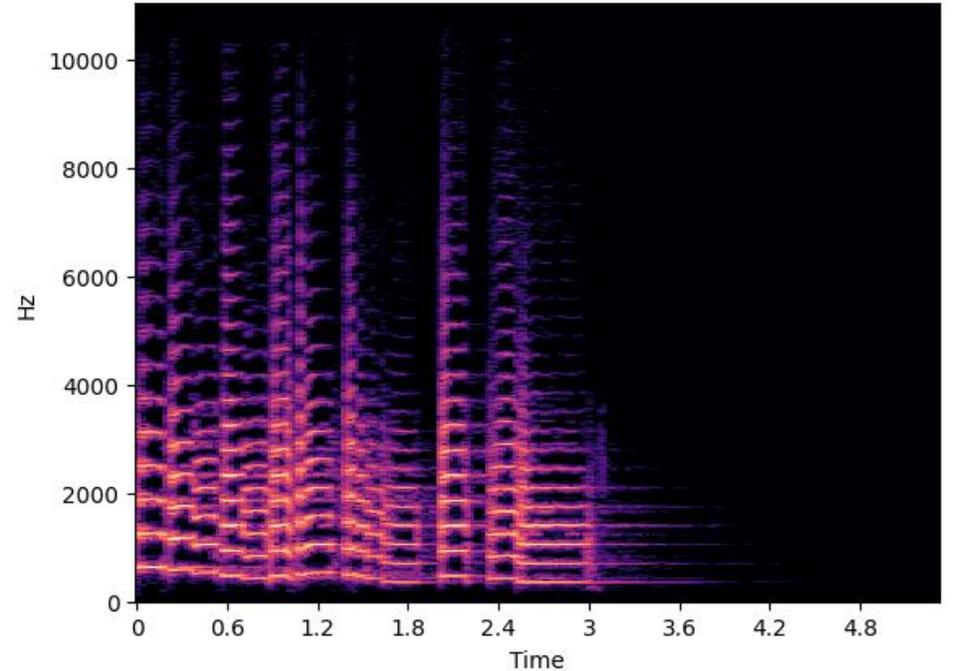
**Fourier Transform cannot localize!**

# Short-Time Fourier Transform (STFT)

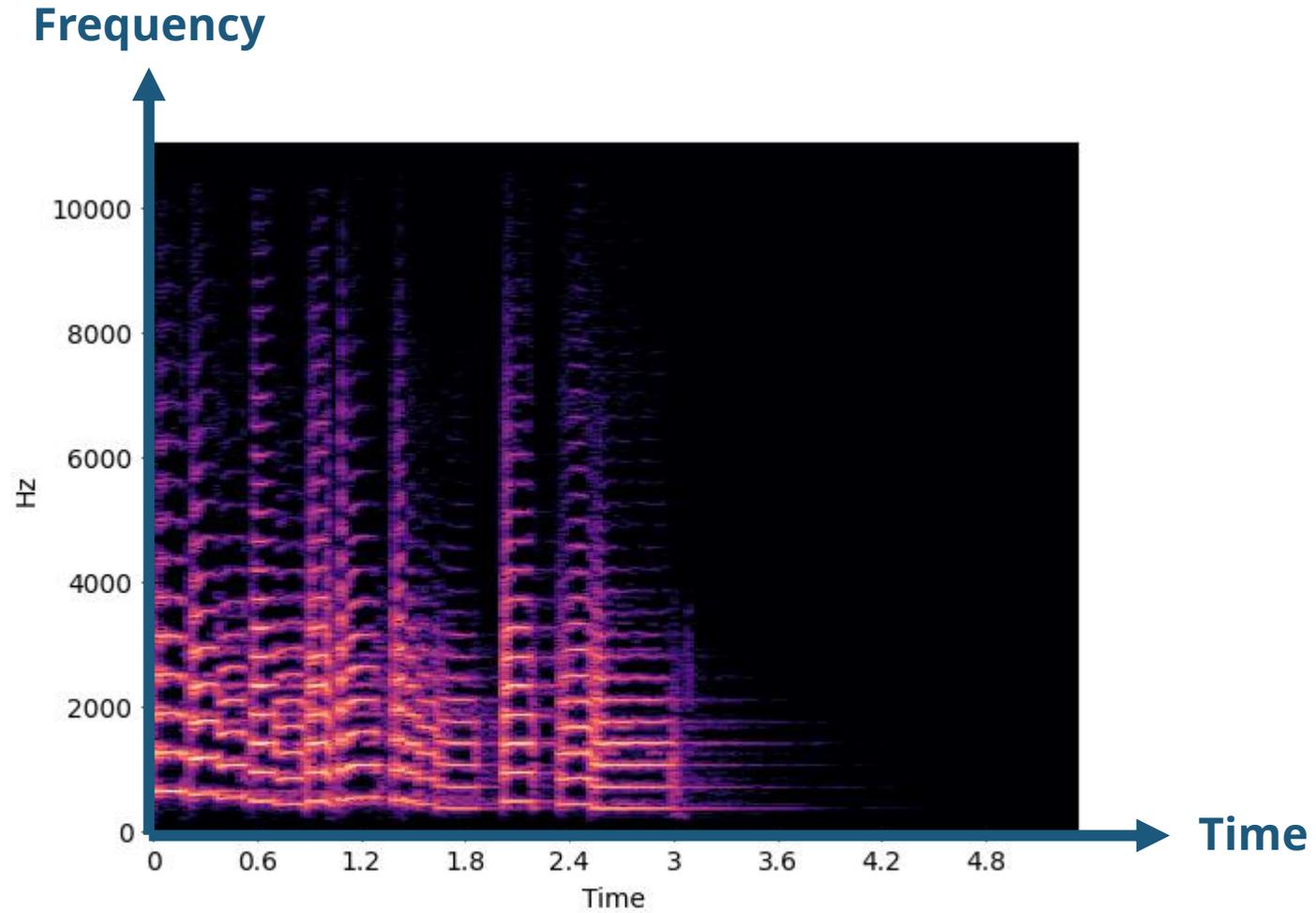
- **Intuition:** Slice the audio into chunks and apply Fourier transform



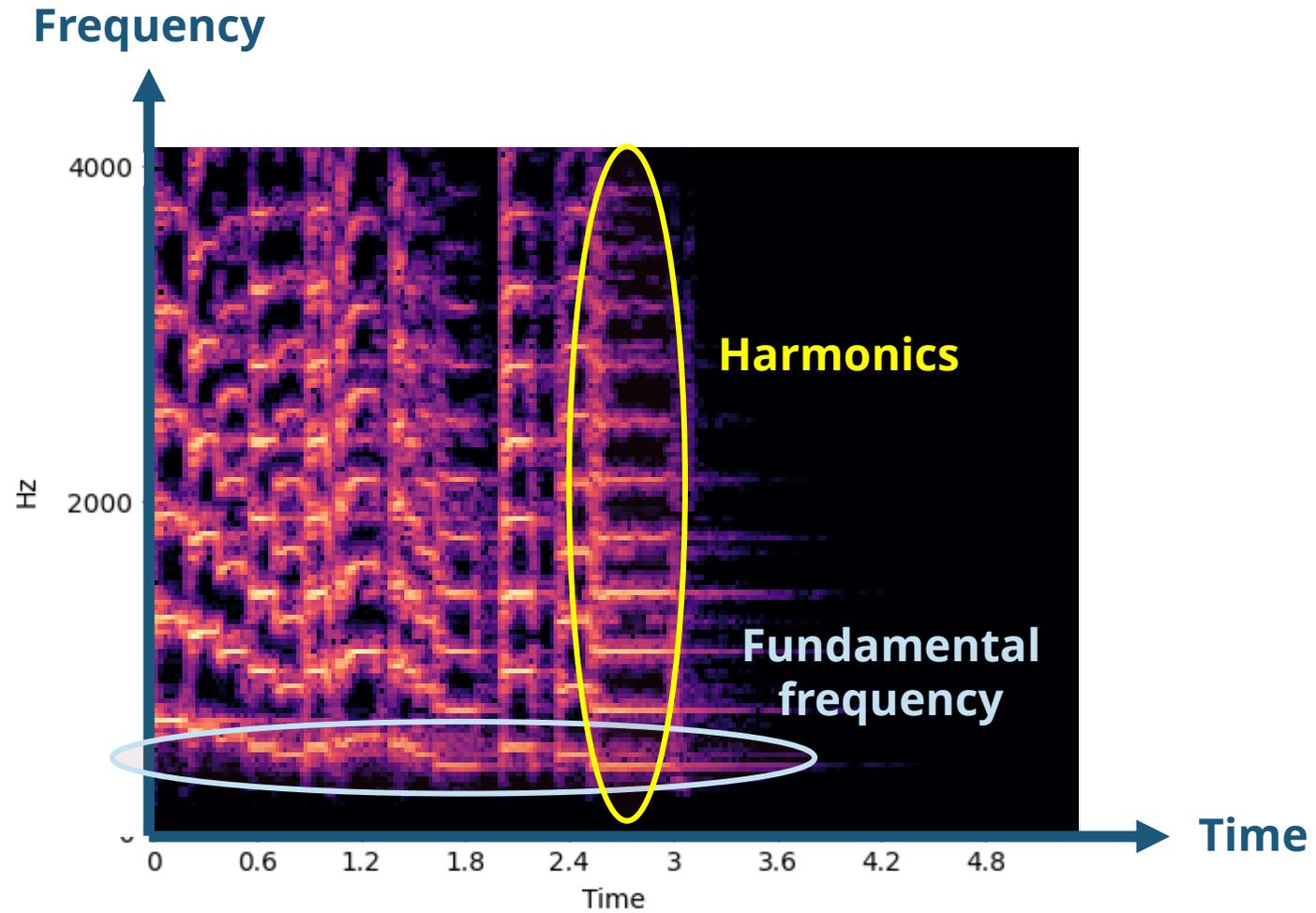
Short-Time  
Fourier  
Transform



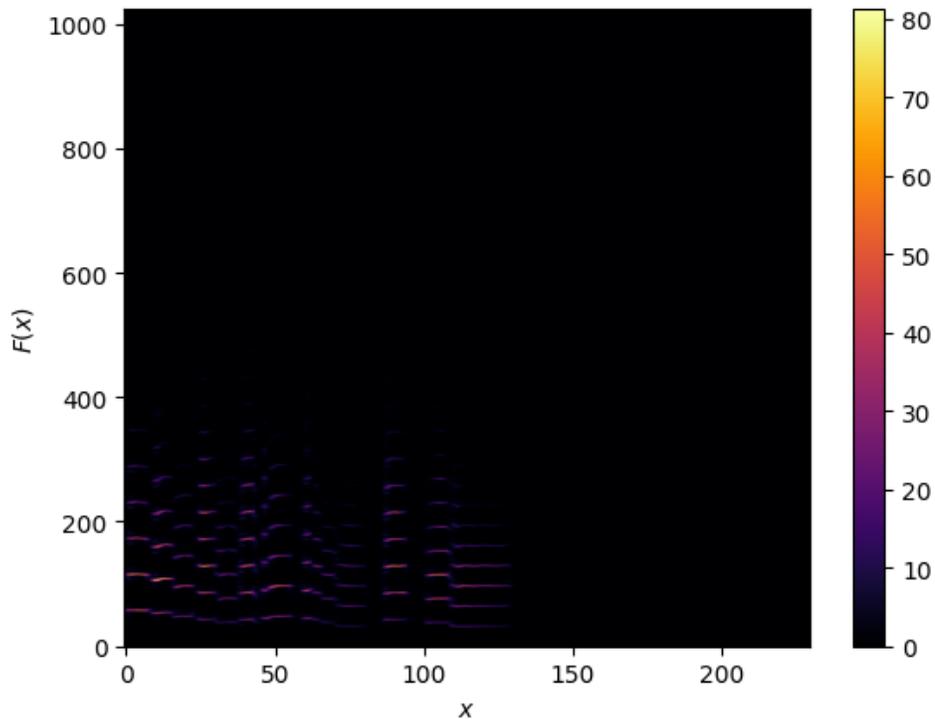
# Spectrogram



# Spectrogram



# Example: librosa.stft



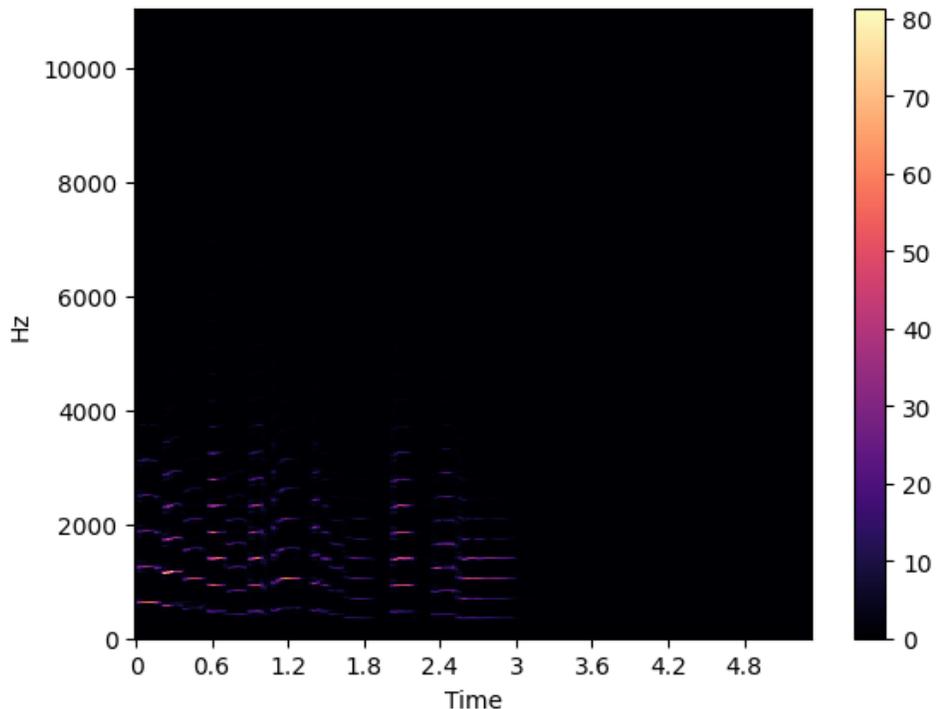
```
# Load the example audio in librosa
y, sr = librosa.load(librosa.example("trumpet"))

# Compute the spectrogram
S = np.abs(librosa.stft(y))

# Plot the spectrogram
im = plt.imshow(S, cmap="inferno", aspect="auto",
                origin="lower")

plt.colorbar(im)
plt.xlabel("Time (sec)")
plt.ylabel("Frequency (Hz)")
plt.show()
```

# Example: `librosa.display.specshow`



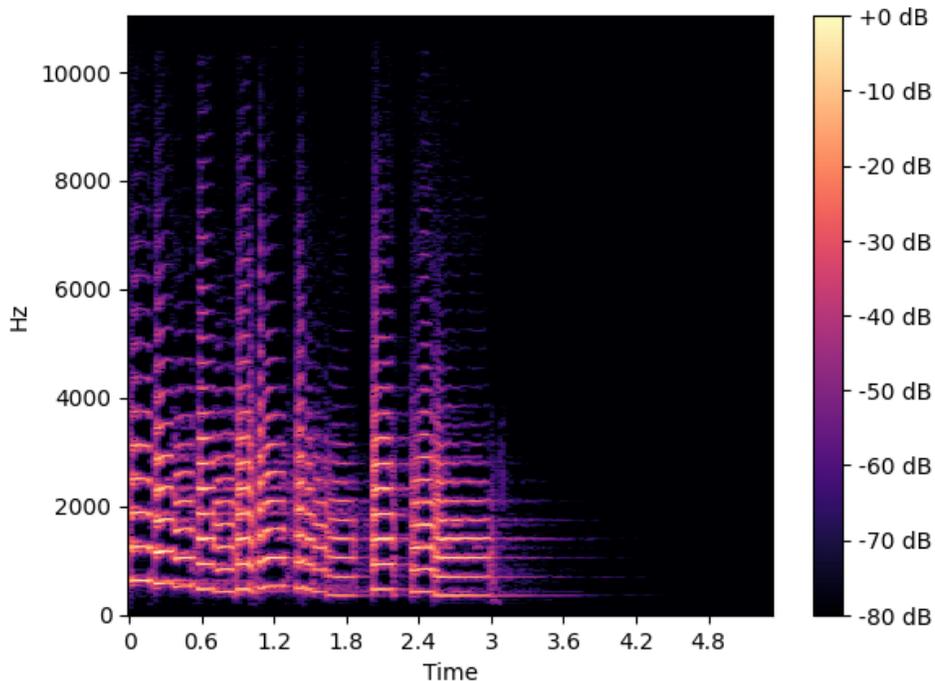
```
# Load the example audio in librosa
y, sr = librosa.load(librosa.example("trumpet"))

# Compute the spectrogram
S = np.abs(librosa.stft(y))

# Plot the spectrogram
im = librosa.display.specshow(S, x_axis="time",
                               y_axis="linear")

plt.colorbar(im)
plt.show()
```

# Example: `librosa.amplitude_to_db`



```
# Load the example audio in librosa
y, sr = librosa.load(librosa.example("trumpet"))

# Compute the spectrogram
S = np.abs(librosa.stft(y))
S_db = librosa.amplitude_to_db(S, ref=np.max)

# Plot the spectrogram
im = librosa.display.specshow(S_db, x_axis="time",
                              y_axis="linear")

plt.colorbar(im, format="+2.0f dB")
plt.show()
```

# Timbre

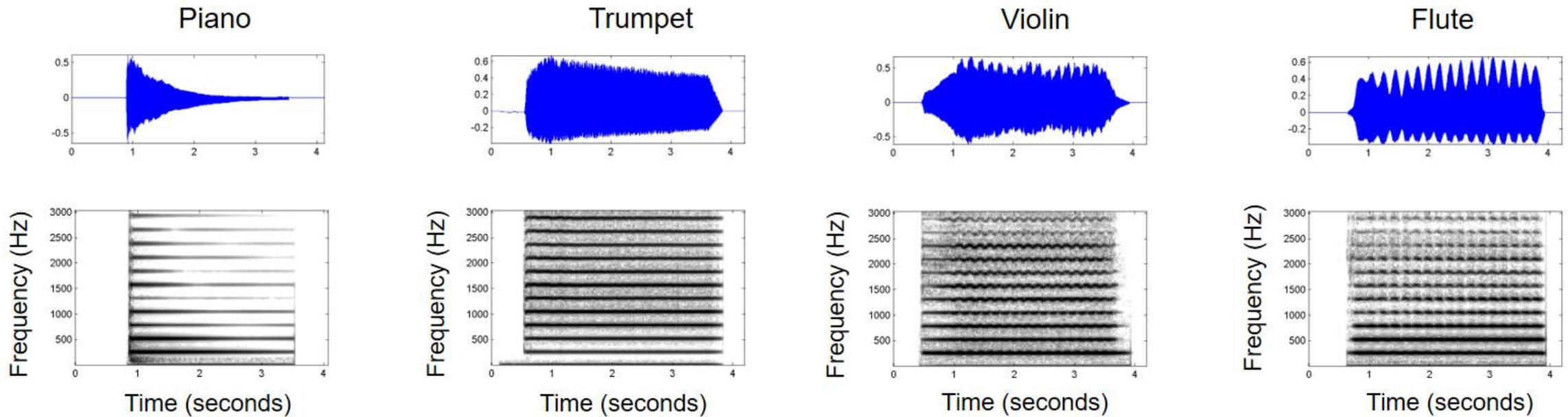
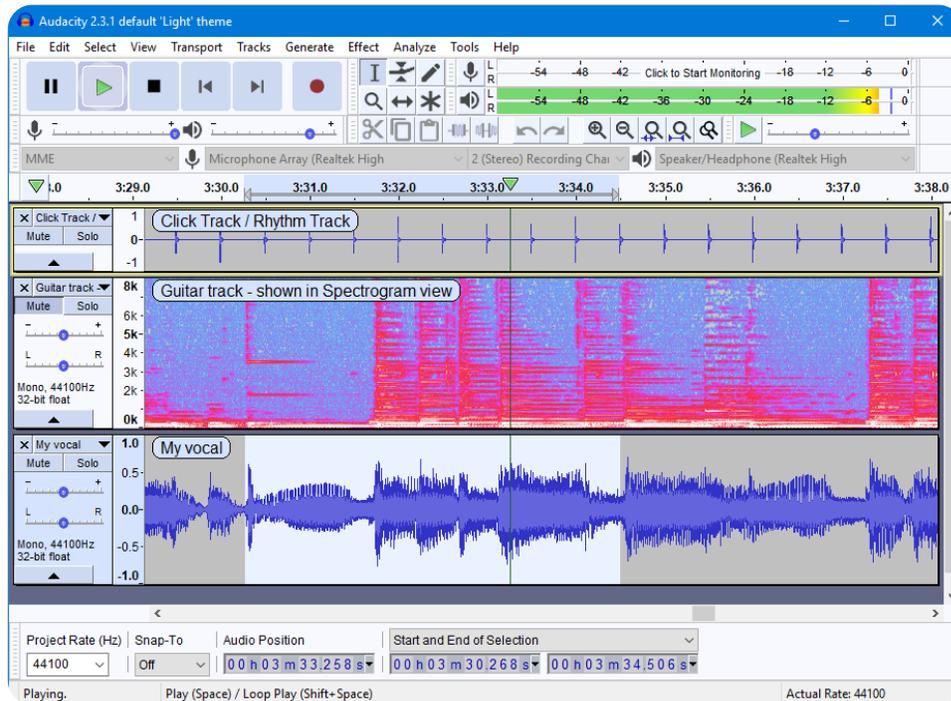


Figure 1.23 from [Müller, FMP, Springer 2015]

(Source: Müller et al., 2021)

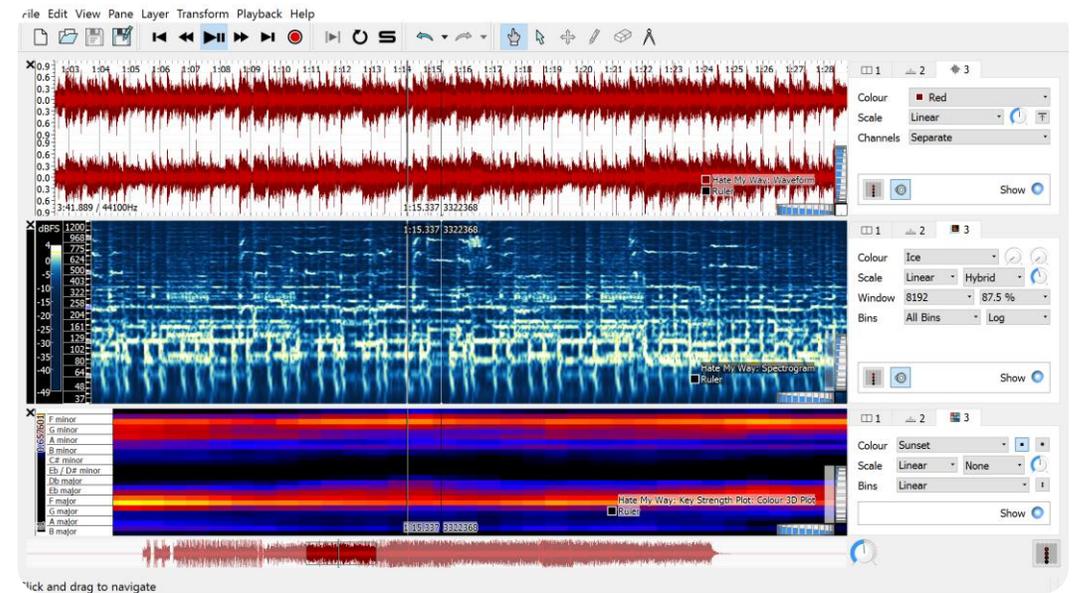
# Software

## Audacity



(Source: audacity-2.3.1 via Internet Archive)

## Sonic Visualiser

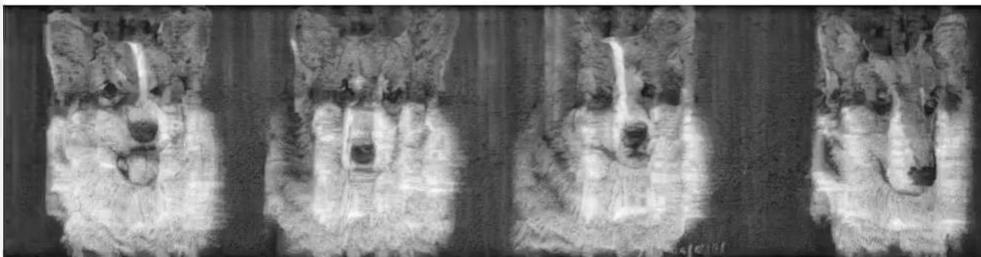


(Source: sonicvisualizer.org)

# Images that Sound (Chen et al., 2024)

Using diffusion models to generate visual spectrograms that look like images but can also be played as sound.

Image prompt: a colorful photo of corgis



Audio prompt: dog barking

(Source: Chen et al., 2024)

Image prompt: a colorful photo of tigers



Audio prompt: tiger growling

(Source: Chen et al., 2024)

# Images that Sound (Chen et al., 2024)

Using diffusion models to generate visual spectrograms that look like images but can also be played as sound.

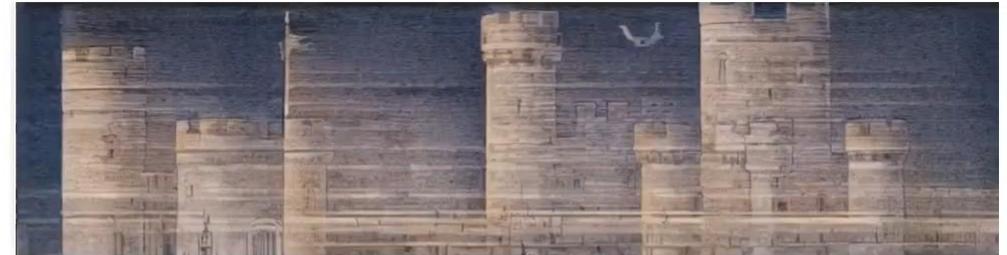
Image prompt: a colorful photo of an auto racing game



Audio prompt: a race car passing by and disappearing

(Source: Chen et al., 2024)

Image prompt: a colorful photo of a castle with bell towers



Audio prompt: bell ringing

(Source: Chen et al., 2024)