



# Signal & Systems

## Lecture 4: Fourier Transform

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## How should we represent signals?

- A signal is information as a function of time
- We want a representation that is:
  - **compact**
  - **reveals structure**
  - **makes system analysis easier**

Goal:  $x(t) \longrightarrow$  useful representation

*Today: we change our viewpoint from time-domain to frequency-domain representations.*

- Any vector can be written as a combination of basis vectors
- Coefficients are **projections**
- Orthogonality makes computations easy

$$\mathbf{x} = a_1\mathbf{e}_1 + a_2\mathbf{e}_2$$

### Signals as infinite-dimensional vectors

$$x(t) = \sum_k a_k \phi_k(t)$$

*Choose basis functions  $\{\phi_k(t)\}$  wisely.*

## Why choose sinusoids as basis?

- Sinusoids are **eigenfunctions** of LTI systems
- They do **not change shape** through an LTI system
- Only amplitude and phase change

$$x(t) = e^{j\omega t} \implies y(t) = H(\omega) e^{j\omega t}$$

Key idea

**Sinusoids “diagonalize” LTI systems.**

## Two complementary views: time vs frequency

### Time domain

- **When** something happens
- Local behavior (transients, edges)
- Convolution describes LTI outputs

### Frequency domain

- **What frequencies** are present
- Global structure (oscillations)
- Multiplication replaces convolution

$$x(t) \text{ (time)} \iff X(\omega) \text{ (frequency)}$$

## Fourier analysis: the idea

- Represent signals by projecting onto complex exponentials
- Periodic signals → **Fourier Series**
- General (aperiodic) signals → **Fourier Transform**

### Periodic: Fourier Series

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_0 t}, \quad \omega_0 = \frac{2\pi}{T}$$

### Aperiodic: Fourier Transform

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$

- A continuous-time signal  $x(t)$  is **periodic** with period  $T > 0$  if

$$x(t + T) = x(t) \quad \forall t$$

- Fundamental (angular) frequency:

$$\omega_0 = \frac{2\pi}{T}$$

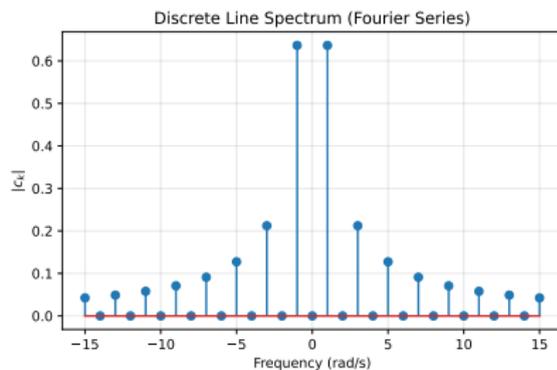
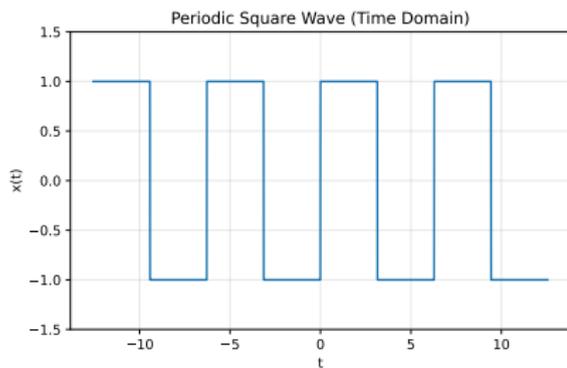
- Examples: sinusoids, square/triangle waves, periodic pulse trains

### Key idea

Periodic signals have a **discrete line spectrum** at harmonics

$$\omega = k\omega_0.$$

# Discrete line spectrum at harmonics



## Why complex exponentials?

- Use the basis functions

$$\phi_k(t) = e^{jk\omega_0 t}, \quad k \in \mathbb{Z}$$

- They are **periodic** with period  $T$  and form an **orthogonal** set over any length- $T$  interval

### Orthogonality (over one period)

$$\frac{1}{T} \int_{t_0}^{t_0+T} e^{jk\omega_0 t} e^{-jm\omega_0 t} dt = \delta_{k,m}$$

$\delta_{k,m}$  is the Kronecker delta: 1 if  $k = m$ , 0 otherwise.

## Representation

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_0 t}$$

- $\{c_k\}$  are complex coefficients (amplitude + phase information)
- Each term corresponds to a harmonic frequency  $k\omega_0$

## Interpretation

$x(t)$  is decomposed into a **weighted sum of harmonically related sinusoids**.

## Fourier Series coefficients

$$c_k = \frac{1}{T} \int_{t_0}^{t_0+T} x(t) e^{-jk\omega_0 t} dt$$

- This is an **inner product** (projection) onto the basis function  $e^{jk\omega_0 t}$
- Orthogonality guarantees:
  - coefficients are uniquely determined (under standard conditions)
  - “no mixing” between different harmonics

$$\langle x, \phi_k \rangle \triangleq \frac{1}{T} \int_{t_0}^{t_0+T} x(t) \phi_k^*(t) dt$$

where  $\phi_k(t) = e^{jk\omega_0 t}$ .

## Signal inner product (over one period)

$$\langle x, y \rangle = \frac{1}{T} \int_{t_0}^{t_0+T} x(t) y^*(t) dt$$

- This satisfies the properties of an inner product:
  - Linearity
  - Conjugate symmetry
  - Positive definiteness
- The Fourier coefficient is a projection:

$$c_k = \langle x(t), e^{jk\omega_0 t} \rangle$$

*Exactly analogous to  $c_k = \mathbf{x}^\top \mathbf{e}_k$  in linear algebra.*

Start from the complex form

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_0 t}$$

- Assume  $x(t)$  is **real-valued**
- Then the coefficients satisfy the conjugate symmetry property:

$$c_{-k} = c_k^*$$

Why?

If  $x(t)$  is real, its complex exponential terms must pair up to produce a real signal.

## Step 2: Separate positive and negative frequencies

Rewrite the series:

$$x(t) = c_0 + \sum_{k=1}^{\infty} \left( c_k e^{jk\omega_0 t} + c_{-k} e^{-jk\omega_0 t} \right)$$

Using  $c_{-k} = c_k^*$ :

$$x(t) = c_0 + \sum_{k=1}^{\infty} \left( c_k e^{jk\omega_0 t} + c_k^* e^{-jk\omega_0 t} \right)$$

Key idea

Positive and negative frequencies form conjugate pairs.

## Step 3: Convert exponentials to sine and cosine

Let

$$c_k = \alpha_k + j\beta_k$$

Using Euler's identity:

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

We obtain:

$$c_k e^{jk\omega_0 t} + c_k^* e^{-jk\omega_0 t} = 2\Re\{c_k\} \cos(k\omega_0 t) - 2\Im\{c_k\} \sin(k\omega_0 t)$$

**Important**

Each conjugate pair produces one cosine and one sine.

## Step 4: Define real Fourier coefficients

Define:

$$a_k = 2\Re\{c_k\}, \quad b_k = -2\Im\{c_k\}$$

and

$$a_0 = c_0$$

Then the series becomes:

$$x(t) = a_0 + \sum_{k=1}^{\infty} \left[ a_k \cos(k\omega_0 t) + b_k \sin(k\omega_0 t) \right]$$

### Conclusion

The sine/cosine form is just the real-valued version of the complex Fourier Series.

Fourier Series gives a **discrete** set of frequency components:

$$\omega = k\omega_0, \quad k \in \mathbb{Z}$$

- Magnitude:  $|c_k|$  tells “how much” of harmonic  $k$
- Phase:  $\angle c_k$  tells alignment / timing information

### Takeaway

Fourier Series  $\Rightarrow$  periodic signals  $\leftrightarrow$  **discrete** frequency representation.

Let  $S_N(t) = \sum_{k=-N}^N c_k e^{jk\omega_0 t}$  be the  $N$ -term partial sum.

- For many signals,  $S_N(t) \rightarrow x(t)$  as  $N \rightarrow \infty$  (pointwise except at discontinuities)
- At a jump discontinuity:

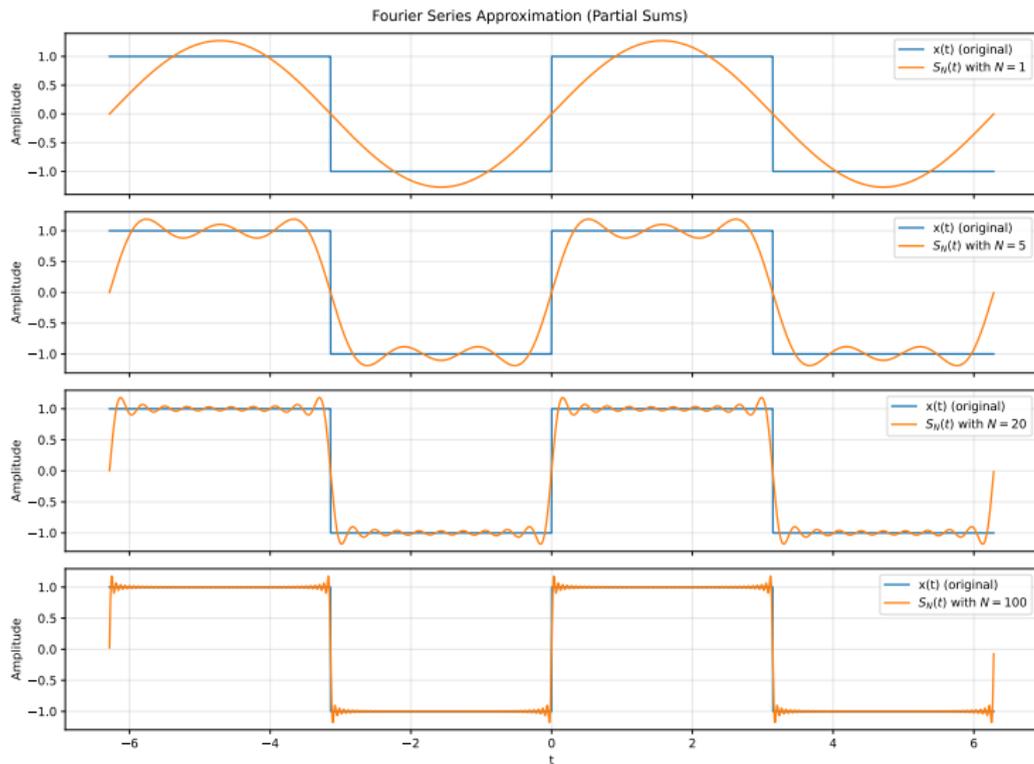
$$S_N(t) \rightarrow \frac{x(t^-) + x(t^+)}{2}$$

- Near discontinuities: **ringing** and **overshoot** (Gibbs)

### Why it matters

FS is a powerful model, but it has limitations.

# Gibbs phenomenon: example



## Discrete frequencies

For a periodic signal with period  $T$ :

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_0 t}$$

where

$$\omega_0 = \frac{2\pi}{T}$$

Therefore the signal contains frequencies

$$\omega = k\omega_0$$

- Only **harmonics of the fundamental frequency** appear
- The spectrum is **discrete**

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- The spectrum is **discrete**

**What happens when the period becomes very large?  $T \rightarrow \infty$ ?**

## When the period grows

Recall

$$\omega_0 = \frac{2\pi}{T}$$

- If  $T$  increases, the spacing between spectral lines decreases

$$\omega_0 \downarrow$$

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## When the period grows

Recall

$$\omega_0 = \frac{2\pi}{T}$$

- If  $T$  increases, the spacing between spectral lines decreases

$$\omega_0 \downarrow$$

- Frequencies become more densely packed
- In the limit

$$T \rightarrow \infty$$

the frequency spacing goes to zero

$$\omega_0 \rightarrow 0$$

## Result

The discrete spectrum becomes a **continuous spectrum**.

## Fourier Series

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_0 t}$$

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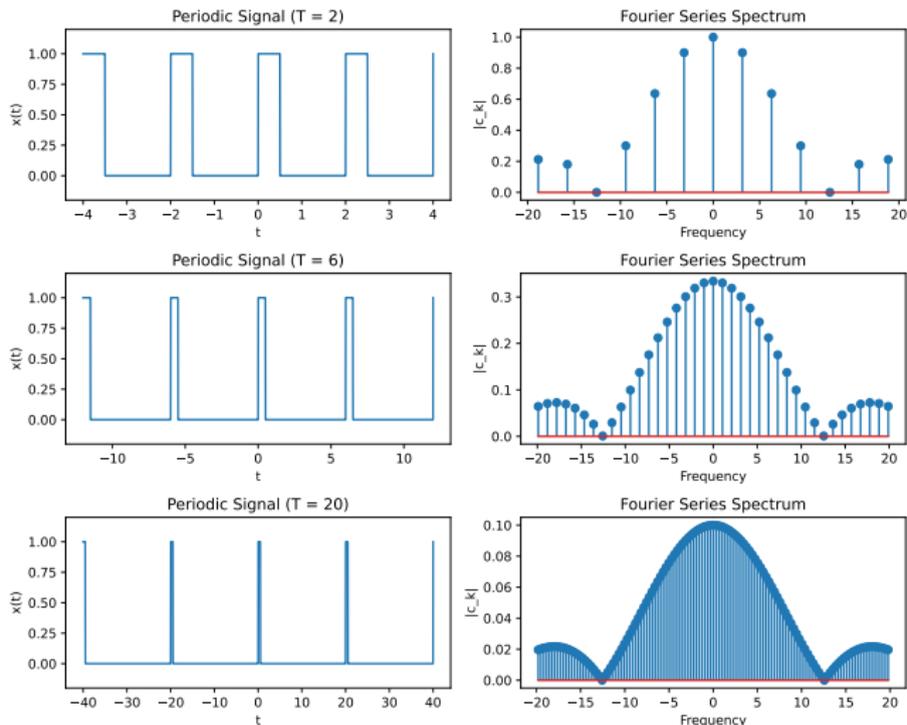
The sum becomes an integral:

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$

### Fourier Transform

A representation for **non-periodic signals**.

# Fourier Series approximations as $T$ grows



# Fourier Series vs Fourier Transform

## Fourier Series

Periodic signal

Discrete frequencies ( $k\omega_0$ )

Coefficients  $c_k$

$$x(t) = \sum_k c_k e^{jk\omega_0 t}$$

## Fourier Transform

Aperiodic signal

Continuous frequencies ( $\omega$ )

Spectrum  $X(\omega)$

$$x(t) = \frac{1}{2\pi} \int X(\omega) e^{j\omega t} d\omega$$

## Forward Fourier Transform

For a signal  $x(t)$  (possibly complex), its Fourier Transform is

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$

## Inverse Fourier Transform

The original signal can be recovered from its spectrum:

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$

- $x(t)$ : time-domain signal
- $X(\omega)$ : frequency-domain representation (spectrum)
- $\omega$ : angular frequency (rad/s)

### Definition

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$
$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$

- Many useful transforms appear repeatedly
- We often reason using **known transform pairs**

### Idea

If we know the transform of a signal, we automatically know the inverse relationship.

## Transform Pair: Impulse and Constant

$$\delta(t) \longleftrightarrow 1$$

$$1 \longleftrightarrow 2\pi\delta(\omega)$$

- An impulse in time contains **all frequencies equally**
- A constant signal contains **only zero frequency**

### Physical meaning

Perfect localization in time  $\Rightarrow$  complete spread in frequency.

## Example: Impulse Signal

Consider the impulse signal

$$x(t) = \delta(t)$$

Compute its Fourier Transform:

$$X(\omega) = \int_{-\infty}^{\infty} \delta(t) e^{-j\omega t} dt$$

Using the sifting property of the impulse:

$$\int_{-\infty}^{\infty} \delta(t) f(t) dt = f(0)$$

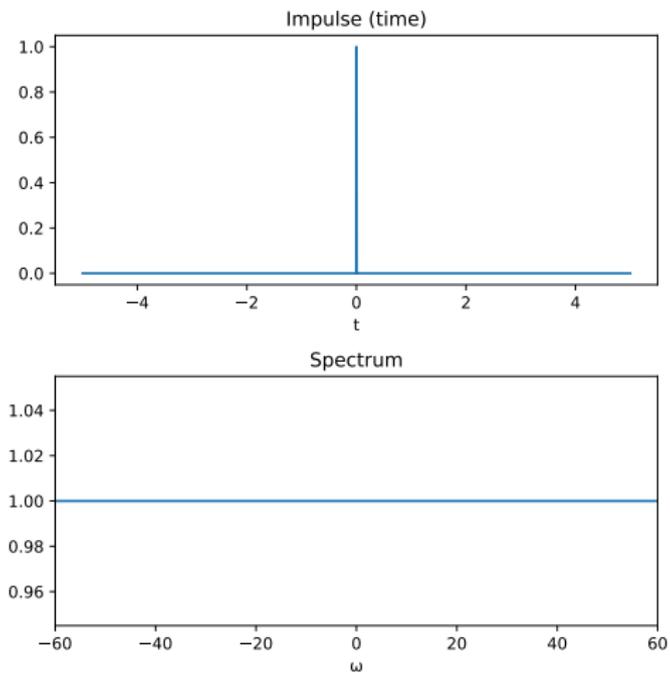
we obtain

$$X(\omega) = e^{-j\omega \cdot 0} = 1$$

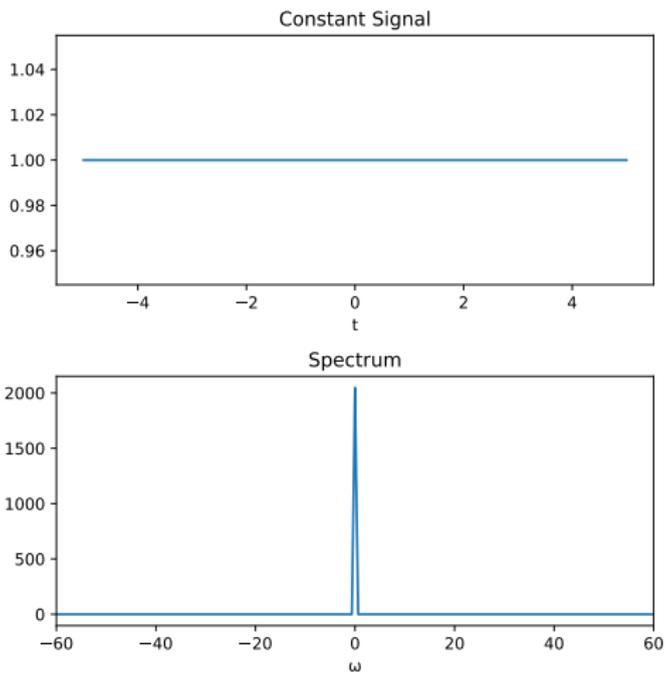
Result

$$\delta(t) \longleftrightarrow 1$$

# Transform Pair: Impulse



## Transform Pair: Constant



## Transform Pair: Rectangular Pulse

$$\text{rect}\left(\frac{t}{T}\right) \longleftrightarrow T \text{sinc}\left(\frac{\omega T}{2}\right)$$

Short pulse in time  $\rightarrow$  wide spectrum

### Key observation

Sharper time localization produces a broader frequency spectrum.

## Example: Rectangular Pulse

Consider the signal

$$x(t) = \begin{cases} 1, & |t| \leq \frac{T}{2} \\ 0, & \text{otherwise} \end{cases}$$

Compute its Fourier Transform:

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$

Since the signal is nonzero only on  $[-T/2, T/2]$ :

$$X(\omega) = \int_{-T/2}^{T/2} e^{-j\omega t} dt$$

## Rectangular Pulse Transform

Compute the integral:

$$\begin{aligned} X(\omega) &= \int_{-T/2}^{T/2} e^{-j\omega t} dt \\ &= \left[ \frac{e^{-j\omega t}}{-j\omega} \right]_{-T/2}^{T/2} \\ &= \frac{e^{-j\omega T/2} - e^{j\omega T/2}}{-j\omega} \end{aligned}$$

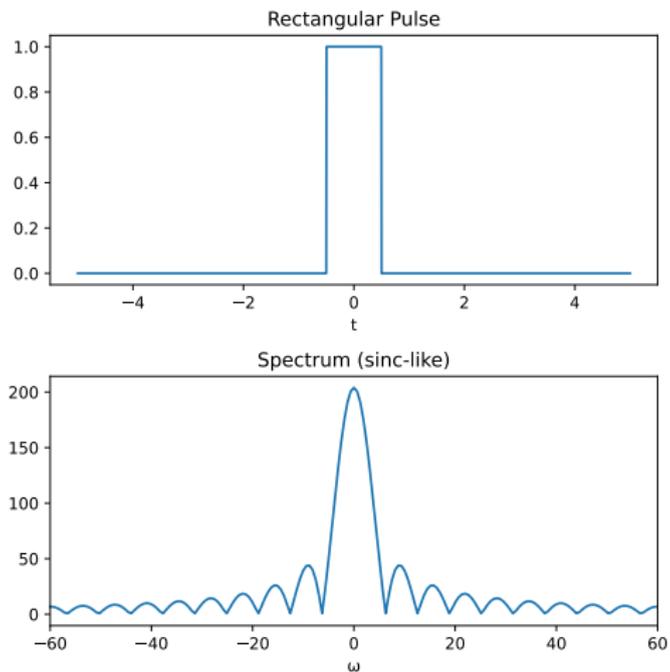
Using

$$e^{j\theta} - e^{-j\theta} = 2j \sin \theta$$

we obtain

$$X(\omega) = T \operatorname{sinc} \left( \frac{\omega T}{2} \right)$$

## Transform Pair: Rectangular Pulse



## Example: Complex Exponential

Consider

$$x(t) = e^{j\omega_0 t}$$

Compute the Fourier Transform:

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$

Substitute  $x(t)$ :

$$X(\omega) = \int_{-\infty}^{\infty} e^{j\omega_0 t} e^{-j\omega t} dt$$

Combine exponents:

$$X(\omega) = \int_{-\infty}^{\infty} e^{-j(\omega - \omega_0)t} dt$$

Consider

$$X(\omega) = \int_{-\infty}^{\infty} e^{-j(\omega-\omega_0)t} dt$$

This integral does not converge in the usual sense.

Instead it is interpreted in the sense of generalized functions:

$$\int_{-\infty}^{\infty} e^{-j\alpha t} dt = 2\pi\delta(\alpha)$$

Applying this identity with  $\alpha = \omega - \omega_0$ :

$$X(\omega) = 2\pi\delta(\omega - \omega_0)$$

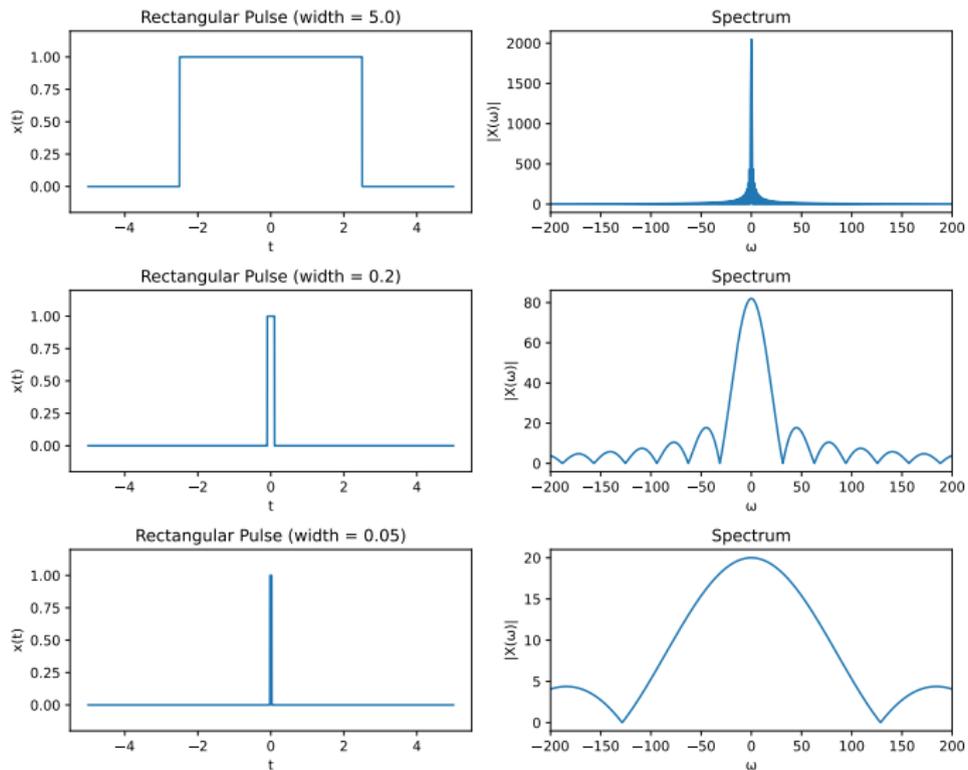
## Time-Frequency Tradeoff

<b>Time domain</b>	<b>Frequency domain</b>
Short signal	Wide spectrum
Long signal	Narrow spectrum
Impulse	All frequencies
Constant/Periodic signal	Single frequency

### Fundamental principle

Signals cannot be simultaneously localized in time and frequency.

# Time-Frequency Tradeoff: Visualization



If

$$x(t) \longleftrightarrow X(\omega)$$

then several useful relationships follow.

- Linearity
- Time shifting
- Modulation (frequency shift)
- Convolution

### Why these matter

They allow us to compute Fourier transforms and analyze systems without directly evaluating integrals.

## Property 1: Linearity

If

$$x_1(t) \leftrightarrow X_1(\omega) \quad x_2(t) \leftrightarrow X_2(\omega)$$

then

$$a x_1(t) + b x_2(t) \longleftrightarrow a X_1(\omega) + b X_2(\omega)$$

### Reason

The Fourier Transform is defined by an integral, which is linear.

### Interpretation

The spectrum of a sum of signals is the sum of their spectra.

## Property 2: Time Shift

If

$$x(t) \leftrightarrow X(\omega)$$

then

$$x(t - t_0) \longleftrightarrow e^{-j\omega t_0} X(\omega)$$

### Interpretation

A time delay does not change the magnitude of the spectrum, but introduces a phase shift.

$$|X(\omega)| \text{ unchanged}$$

$$\angle X(\omega) \rightarrow \angle X(\omega) - \omega t_0$$

## Property 3: Modulation

If

$$x(t) \leftrightarrow X(\omega)$$

then

$$e^{j\omega_0 t} x(t) \longleftrightarrow X(\omega - \omega_0)$$

### Interpretation

Multiplying a signal by a complex sinusoid shifts its spectrum.

This is the basis of modulation in communication systems.

## Property 3: Modulation (2)

Using Euler's identity

$$\cos(\omega_0 t) = \frac{e^{j\omega_0 t} + e^{-j\omega_0 t}}{2}$$

we obtain

$$x(t) \cos(\omega_0 t) \longleftrightarrow \frac{1}{2} \left[ X(\omega - \omega_0) + X(\omega + \omega_0) \right]$$

## Property 3: Modulation (2)

Using Euler's identity

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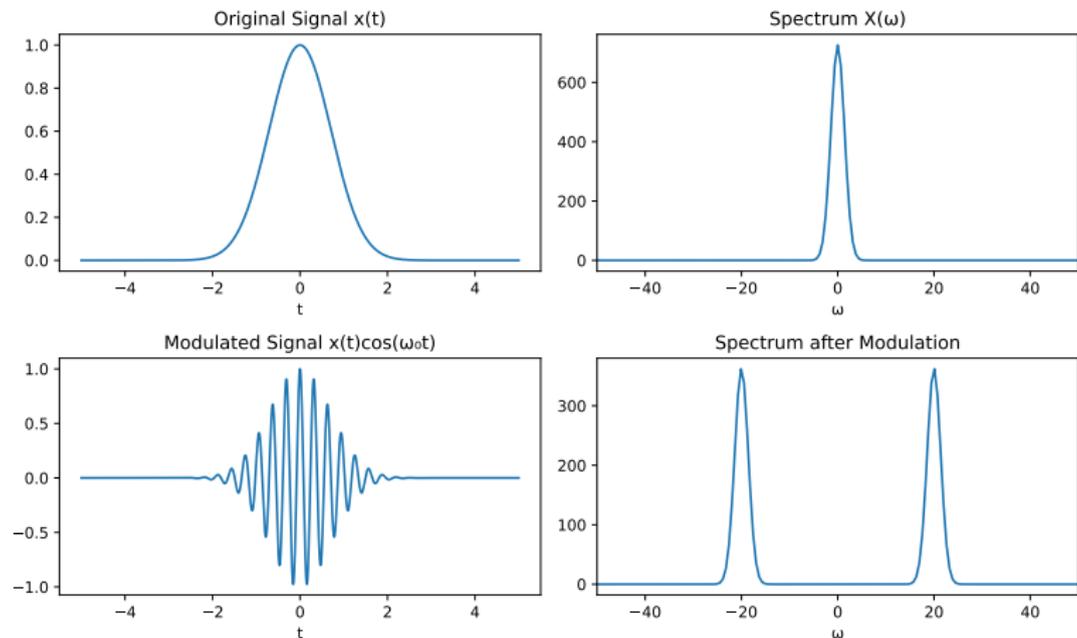
we obtain

$$x(t) \cos(\omega_0 t) \longleftrightarrow \frac{1}{2} \left[ X(\omega - \omega_0) + X(\omega + \omega_0) \right]$$

Similarly,

$$x(t) \sin(\omega_0 t) \longleftrightarrow \frac{1}{2j} \left[ X(\omega - \omega_0) - X(\omega + \omega_0) \right]$$

# Modulation Visualization



# Why Do We Need Modulation?

- Many real-world signals (audio, sensors, speech) are **low-frequency** signals.
- However, wireless communication systems operate at **high frequencies**.

## Example: AM Radio

- Voice signal:  $\approx 300$  Hz—3 kHz
- Radio carrier:  $\approx 1$  MHz

To transmit the signal, we multiply it by a high-frequency carrier:

$$s(t) = x(t) \cos(\omega_c t)$$

This shifts the spectrum to the carrier frequency.

## Result

- The signal can be transmitted efficiently through the air
- Different users can occupy different frequency bands

## Property 4: Convolution

If

$$x(t) \leftrightarrow X(\omega) \quad h(t) \leftrightarrow H(\omega)$$

then

$$x(t) * h(t) \longleftrightarrow X(\omega)H(\omega)$$

and

$$x(t)h(t) \longleftrightarrow \frac{1}{2\pi} X(\omega) * H(\omega)$$

### Key result

Convolution in time becomes multiplication in frequency. Multiplication in time becomes convolution in frequency.

# Additional Fourier Transform Properties

If

$$x(t) \longleftrightarrow X(\omega)$$

then the following useful properties also hold:

- **Time Scaling**

$$x(at) \longleftrightarrow \frac{1}{|a|} X\left(\frac{\omega}{a}\right)$$

- **Differentiation in Time**

$$\frac{d}{dt}x(t) \longleftrightarrow j\omega X(\omega)$$

- **Integration in Time**

$$\int_{-\infty}^t x(\tau) d\tau \longleftrightarrow \frac{1}{j\omega} X(\omega)$$

- **Parseval's Theorem**

$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\omega)|^2 d\omega$$

- **Duality**

$$x(t) \longleftrightarrow X(\omega) \quad \Rightarrow \quad X(t) \longleftrightarrow 2\pi x(-\omega)$$

Any Fourier Transform can be written as

$$X(\omega) = |X(\omega)|e^{j\angle X(\omega)}$$

- $|X(\omega)|$  : **Magnitude spectrum**
- $\angle X(\omega)$  : **Phase spectrum**

## Interpretation

- Magnitude tells **how much** of each frequency exists
- Phase tells **how those frequencies align in time**

# Computing the Phase of a Spectrum

The Fourier Transform is generally complex:

$$X(\omega) = \Re\{X(\omega)\} + j \Im\{X(\omega)\}$$

We can express it in polar form:

$$X(\omega) = |X(\omega)|e^{j\angle X(\omega)}$$

## Magnitude

$$|X(\omega)| = \sqrt{(\Re\{X(\omega)\})^2 + (\Im\{X(\omega)\})^2}$$

## Phase

$$\angle X(\omega) = \arctan\left(\frac{\Im\{X(\omega)\}}{\Re\{X(\omega)\}}\right)$$

## In practice

Use the function  $\text{atan2}(\Im, \Re)$  to obtain the correct phase quadrant.

## What Does the Magnitude Tell Us?

- The magnitude spectrum indicates the **strength of each frequency**

$$|X(\omega)|$$

Large value  $\Rightarrow$  strong presence of that frequency

### Example

A signal with sharp transitions requires many high frequencies.

## What Does the Phase Tell Us?

$$\angle X(\omega)$$

- Phase determines how frequency components align in time
- Changing phase can shift or reshape the signal

### Example

A time shift produces a linear phase shift:

$$x(t - t_0) \longleftrightarrow e^{-j\omega t_0} X(\omega)$$

Suppose we reconstruct a signal using:

- Correct magnitude but random phase
- Correct phase but incorrect magnitude

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- Correct magnitude but random phase
- Correct phase but incorrect magnitude

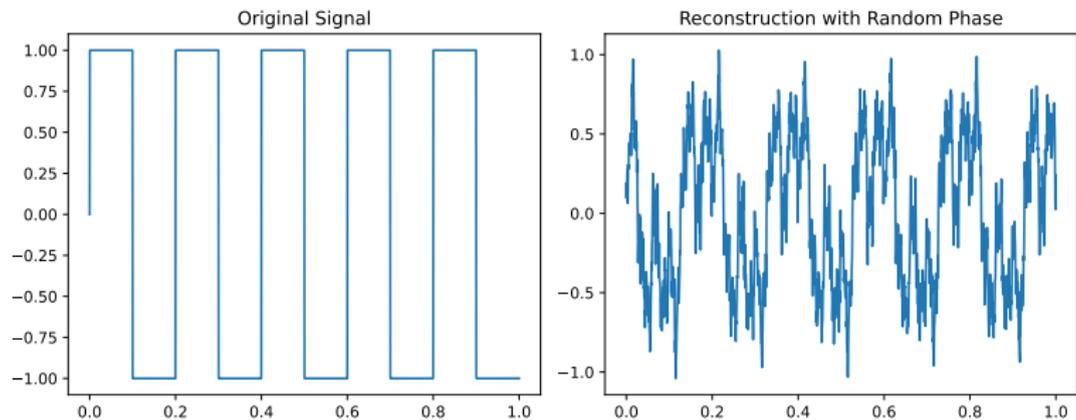
### Observation

Phase often carries much of the signal structure.

Magnitude: **how much**

Phase: **where**

# Magnitude vs Phase: Example



## Magnitude vs Phase: Example (2)

Image 1



Magnitude 1 + Phase 2



Image 2



Magnitude 2 + Phase 1



- **Any Questions?**
- **Office Hours:**
  - **Mon & Tue** (09:00-11:00)
  - 24/7 by email ([costashatz@upatras.gr](mailto:costashatz@upatras.gr), subject: *ECE\_SS\_AM*)
- **Material and Announcements**



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