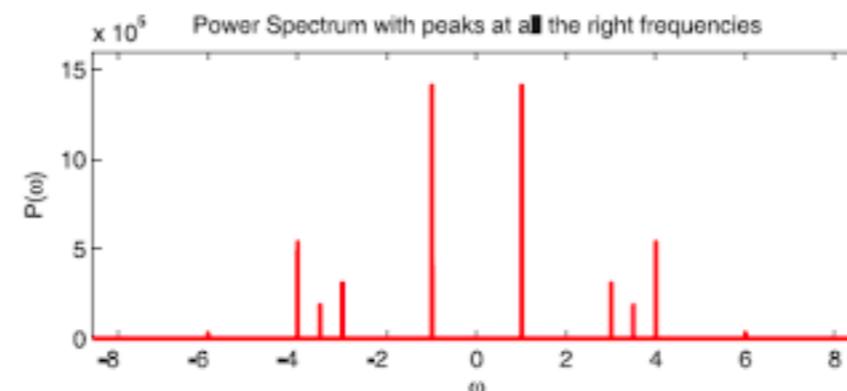


# Question of the Day

Can you play a song from knowing its DFT or power spectrum?



G A B D

Musical notation for the song "Mary Had a Little Lamb". The notes are numbered 1 through 7 above them. The notation consists of seven measures of quarter notes in common time, starting with a treble clef. The notes are grouped by measure, with measure numbers 1 through 7 placed above each group of four notes.

Mary Had a Little Lamb

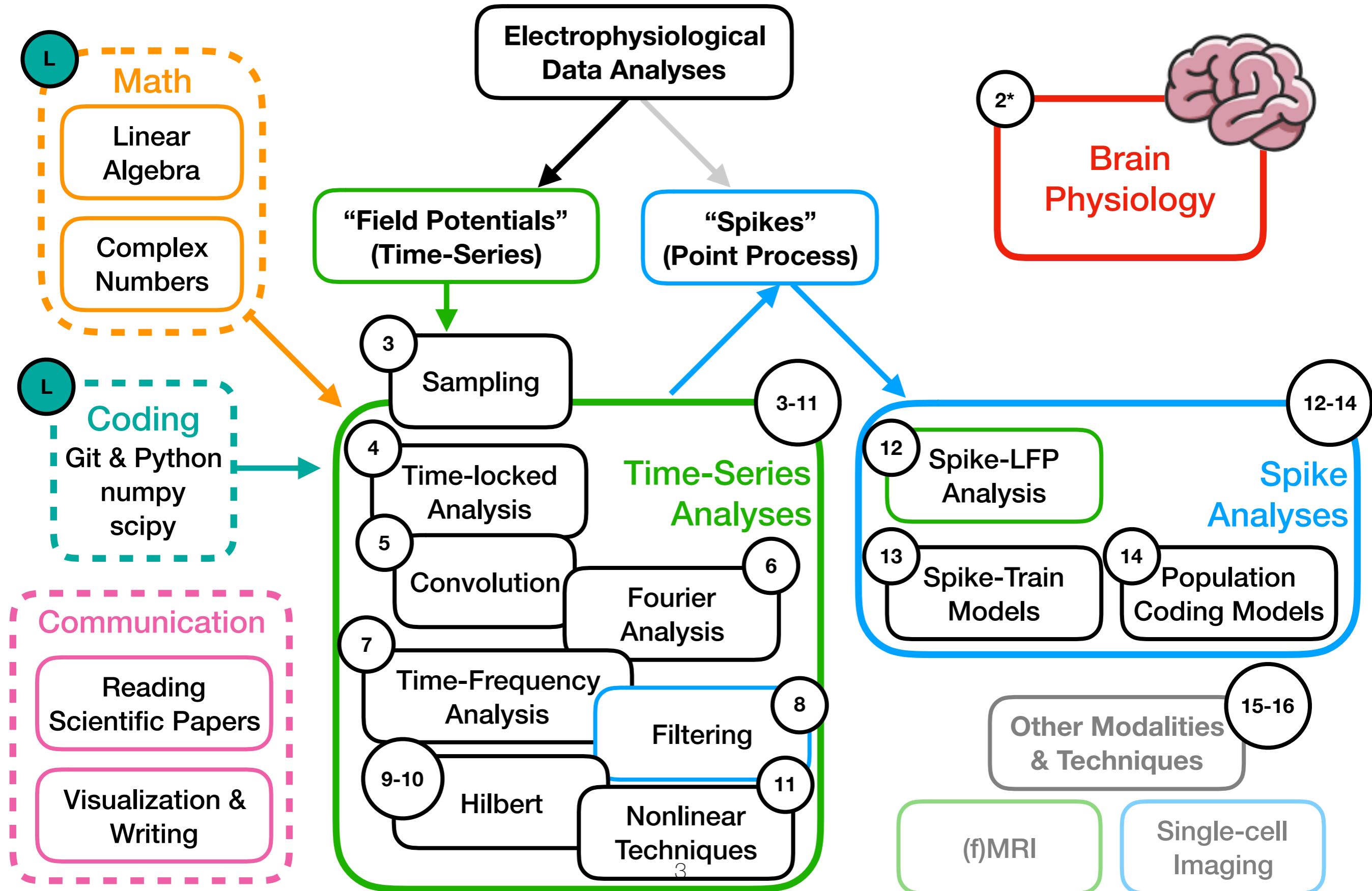


## Fourier Part II & Time-Frequency Analysis

Lecture 7  
July 11, 2019



# Course Outline: Road Map



1. Some Fourier properties
2. Computing frequency from wave number
3. Time-frequency analysis



# Handy Properties of DFT

**Linearity**

**Orthogonality**

**Periodicity**

**Duality**

**(Circular) Convolution Theorem**

**Power Conservation (Parseval's Theorem)**



$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$

if  $F\{x(n)\}_k = X_k, F\{y(n)\}_k = Y_k$

$$F(\{ax(n) + by(n)\})_k = aX_k + bY_k$$

Because the **dot product is a linear** operation.

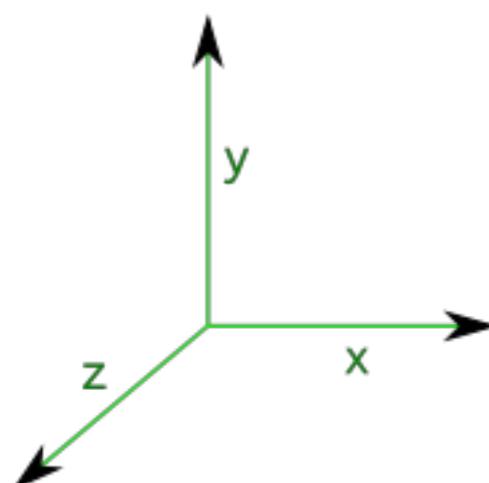


# Orthogonality

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$

for wave numbers k and m:

$$\text{dot}\left(e^{\frac{i2\pi n}{N}k}, e^{\frac{i2\pi n}{N}m}\right) = 0 \text{ if } k \neq n, = 1 \text{ if } k = n$$



The complex exponentials of all k combine to form an N-dimensional orthogonal basis.



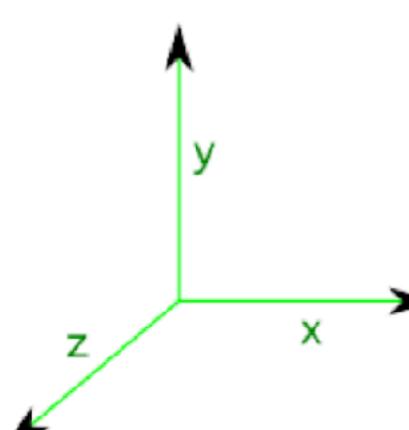
# Orthogonality

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$

for wave numbers k and m:

$\text{dot}(e^{\frac{i2\pi n}{N} k}, e^{\frac{i2\pi n}{N} m}) = 0 \text{ if } k \neq n, = 1 \text{ if } k = n$

vector


$$e^{\frac{i2\pi k}{N} [0, 1, 2, \dots, N-1]}$$
$$\Rightarrow [e^{\frac{i2\pi}{N} 0}, [ ], [ ]^1, [ ]^2, \dots]$$



# Periodicity

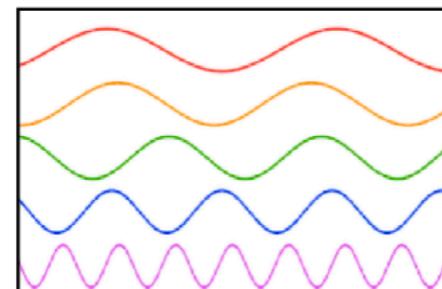
From yesterday:

**Fourier Decomposition:** represent an **infinite-length** signal as the summation of a number of **infinite-length** cosine and sine waves.

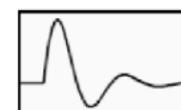
$$\cos(\omega t)$$

$$\sin(\omega t)$$

for  $t \in (-\infty, \infty)$



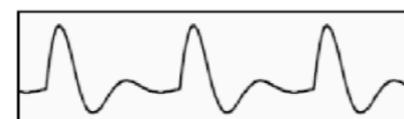
But real life signals are always **finite**.



extend as aperiodic signal (with 0s)



extend as periodic signal



Also from yesterday:

$\{x_n\} := x_0, x_1, \dots, x_{N-1}$  into another sequence of complex numbers,  
 $\{X_k\} := X_0, X_1, \dots, X_{N-1}$ , which is defined by

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$

We can measure the contribution of a single frequency,  $f$ , but which frequencies to include so we can fully decompose the signal?

The answer is in the equation:  **$k$  goes from 0 to  $N-1$**

**You need as many frequencies as you have time points!**

$X_k$  is infinite-length  
(there are infinite # of coefficients)

**$k$  goes from 0 to  $N-1$**   
(there are  $N$  coefficients)

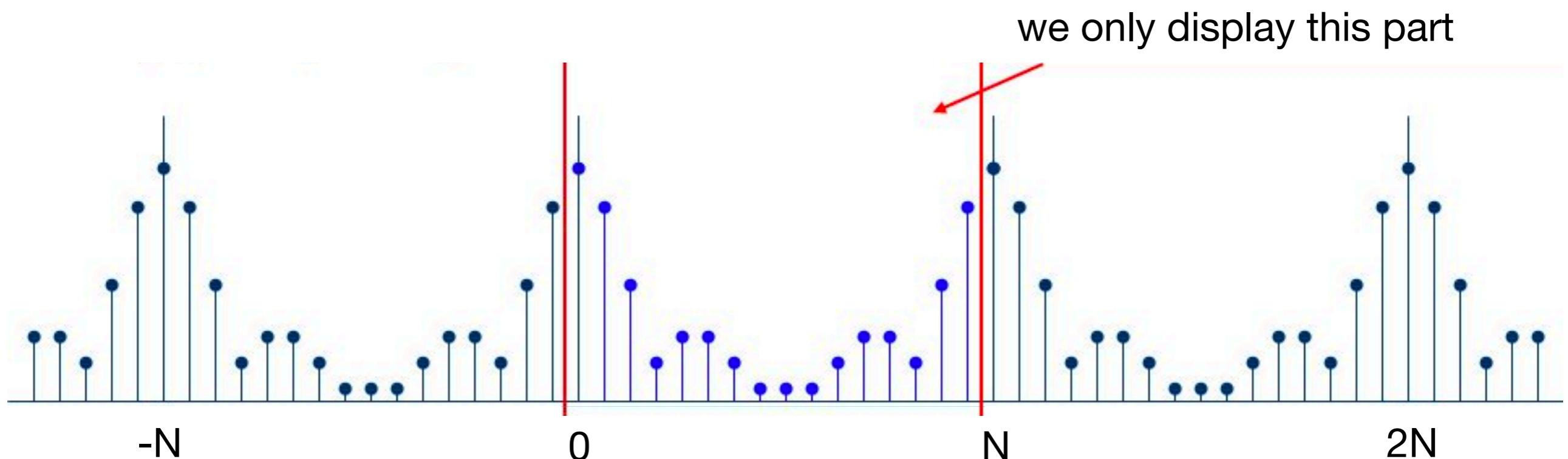
# WTF?



# Periodicity

## **Answer:**

$X_k$  is periodic, with period N.  
->  $k$  repeats itself after every N



# Periodicity

**Answer:**

$X_k$  is periodic, with period N.  
-> k repeats itself after every N

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$



## Answer:

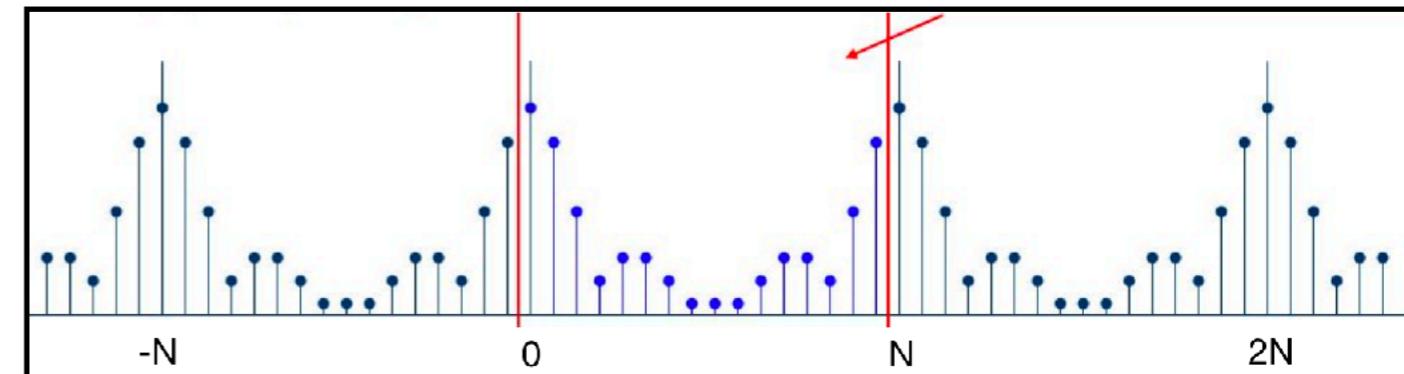
$X_k$  is periodic, with period N.  
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$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \quad (\text{Eq.1})$$

Time Domain



Frequency Domain



DFT transforms an infinite-length periodic signal in time  
to infinite-length periodic signal in frequency



## Fourier Transform

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

## Inverse Fourier Transform

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k \cdot e^{i2\pi kn/N}$$

**They are identical!**  
(up to a constant and sign)

**Implication:** as far as your digital computer is concerned, the sequence of number can be in time or frequency domain.

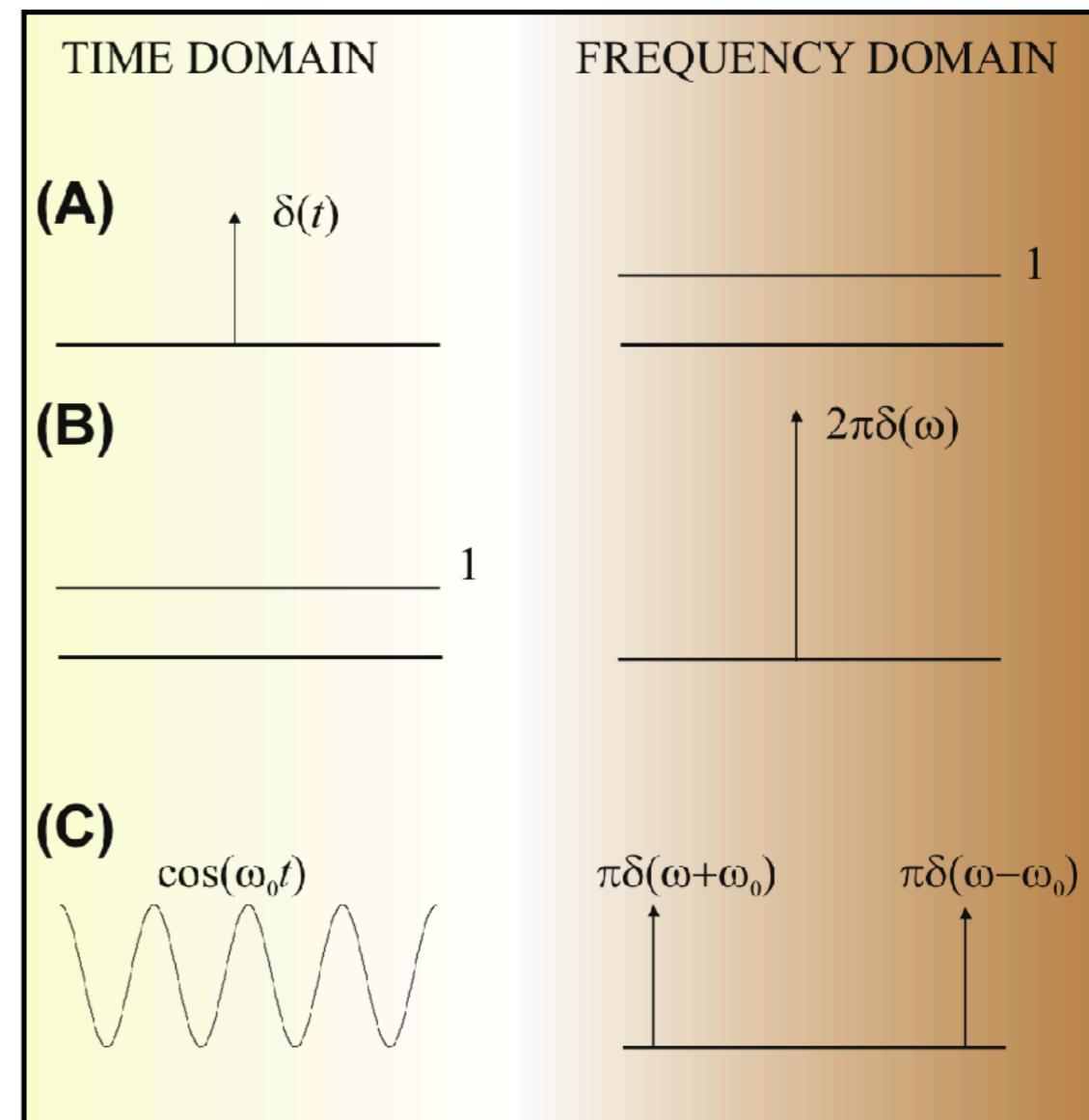


# Fourier Pairs

delta & (co)sines have a special relationship

**TABLE 6.1** Examples of Fourier Transform Pairs

Time/Spatial Domain $f(t)$	Frequency Domain $F(\omega)$
$\delta(t)$	1
1	$2\pi \delta(\omega)$
$\cos(\omega_0 t)$	$\pi[\delta(\omega + \omega_0) + \delta(\omega - \omega_0)]$
$\sin(\omega_0 t)$	$j\pi[\delta(\omega + \omega_0) - \delta(\omega - \omega_0)]$

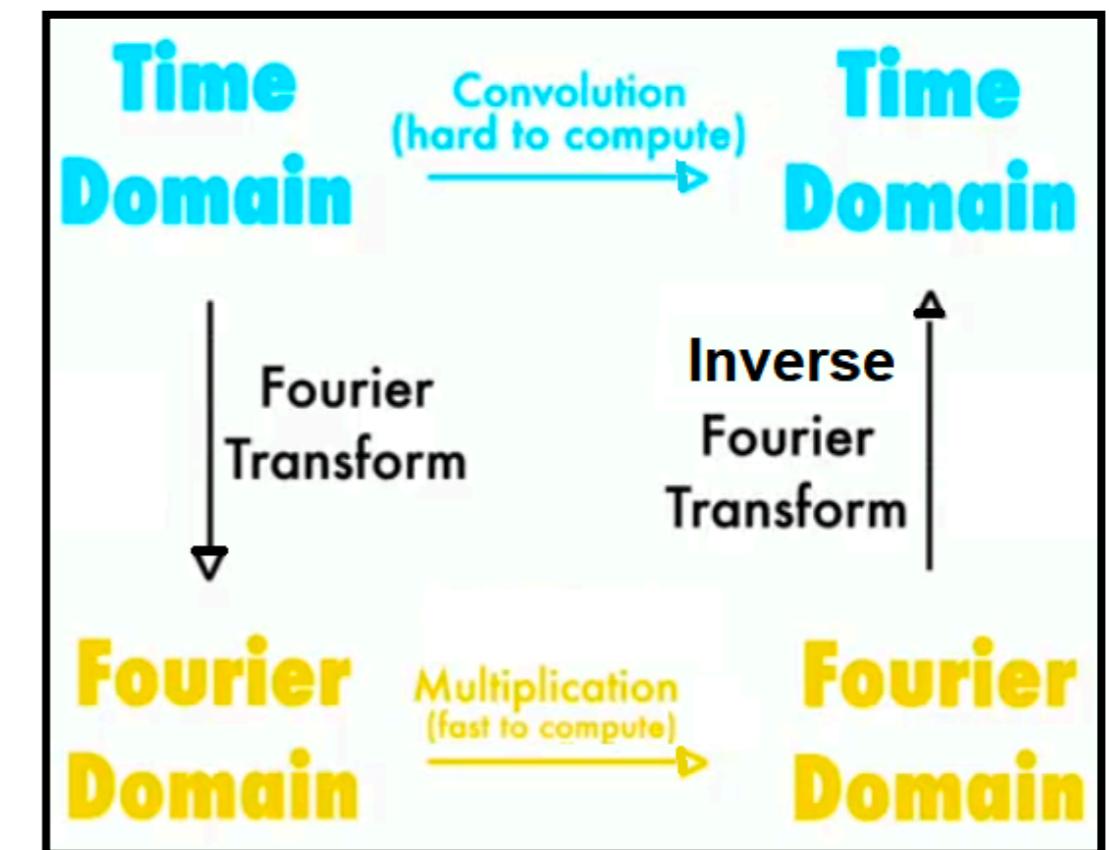
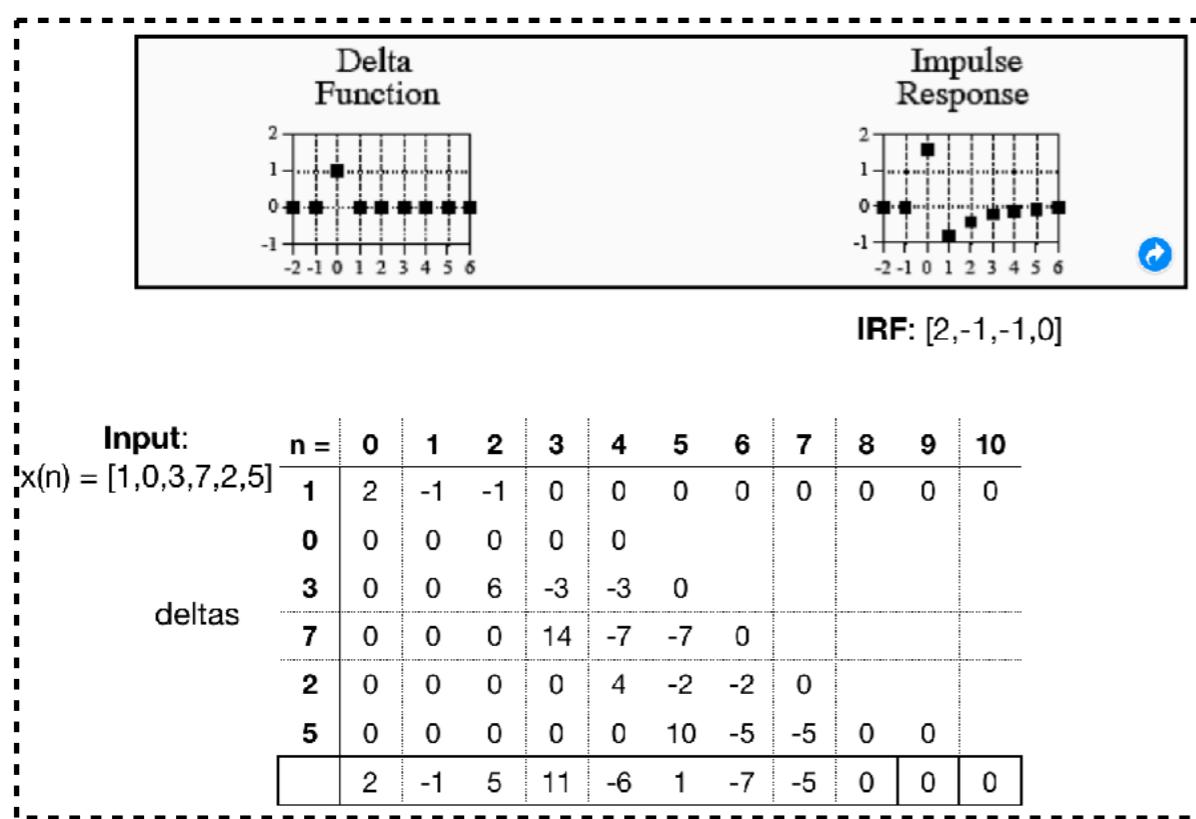


# (Circular) Convolution Theorem

Convolution in time domain is equivalent to multiplication in frequency domain, and the converse is true as well (duality).

x: input  
h: system's IRF  
y: output

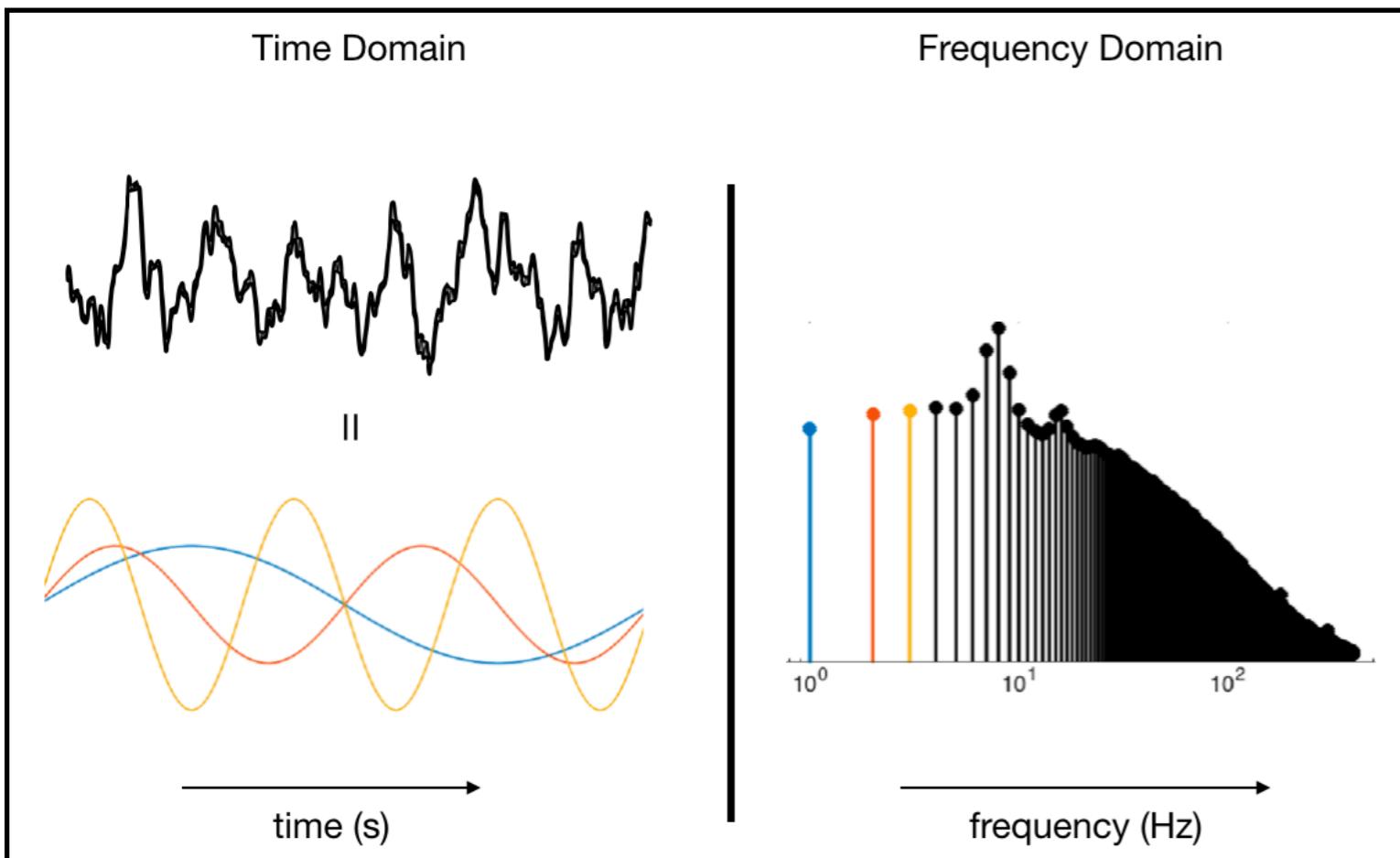
$$x(t) \circledast h(t) = y(t)$$
$$X(f)H(f) = Y(f)$$



# Parseval's Theorem

Power is conserved in from time and frequency domain.

$$\sum_{n=0}^{N-1} |x_n|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X_k|^2$$



Fourier Transform allows us to examine the power at each frequency.

“Spectral Analysis”



# Parseval's Theorem

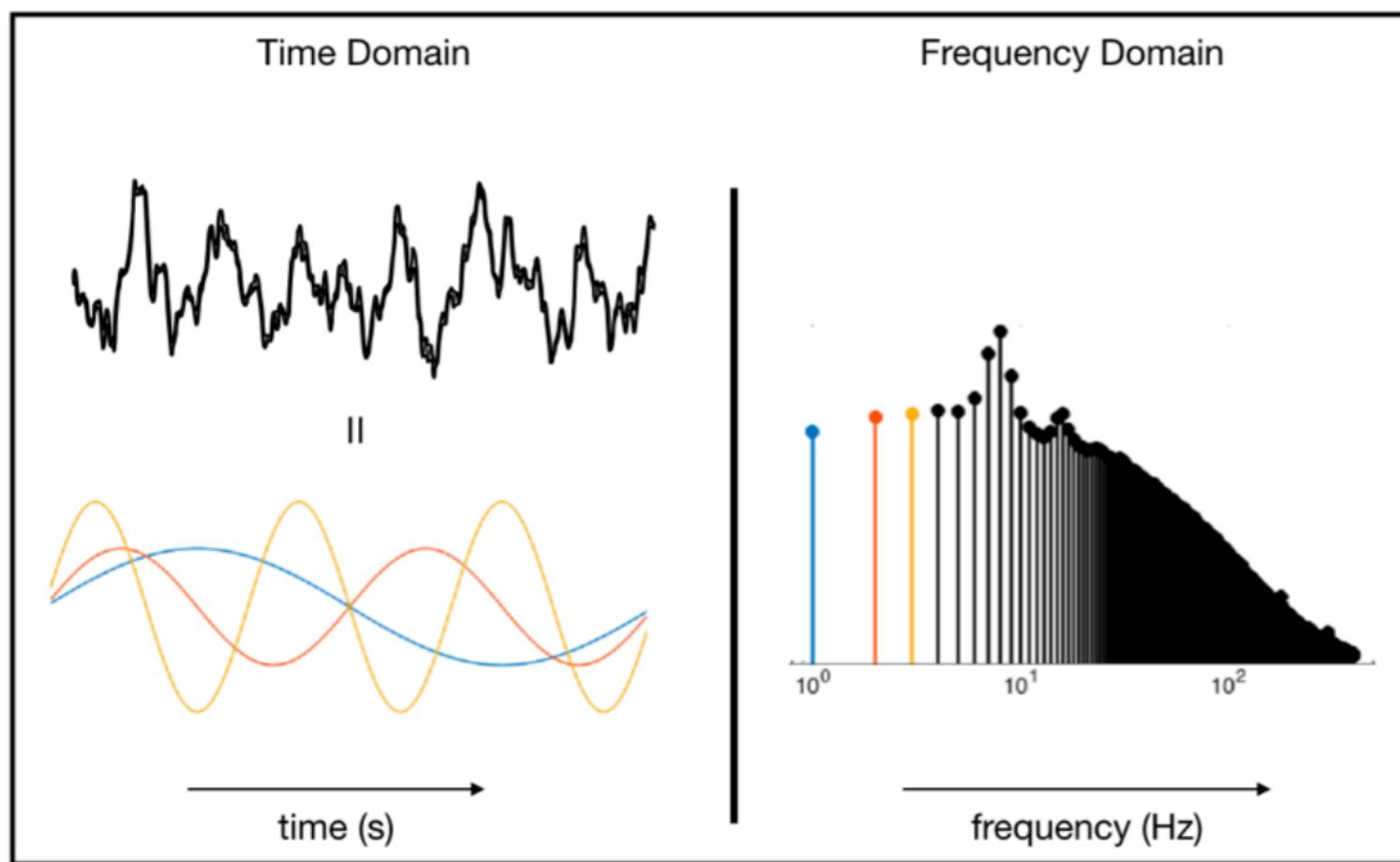
Power is conserved in from time and frequency domain.

$$P(f) = \sqrt{2}$$

$$\sum_{n=0}^{N-1} |x_n|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X_k|^2$$

$$\text{var}(x) = \sum_{n=0}^{N-1} (x_n - \bar{x})^2$$

*mean of  $x$*



# Handy Properties of DFT

**Linearity**

**Orthogonality**

**Periodicity**

**Duality**

**(Circular) Convolution Theorem**

**Power Conservation (Parseval's Theorem)**



1. Some Fourier properties
2. Computing frequency from wave number
3. Time-frequency analysis



# How Many Frequencies?

$\{\mathbf{x}_n\} := x_0, x_1, \dots, x_{N-1}$  into another sequence of complex numbers,  
 $\{\mathbf{X}_k\} := X_0, X_1, \dots, X_{N-1}$ , which is defined by

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)], \end{aligned} \tag{Eq.1}$$

We can measure the contribution of a single frequency,  $f$ , but which frequencies to include so we can fully decompose the signal?

The answer is in the equation:  **$k$  goes from 0 to  $N-1$**

**You need as many frequencies as you have time points!**



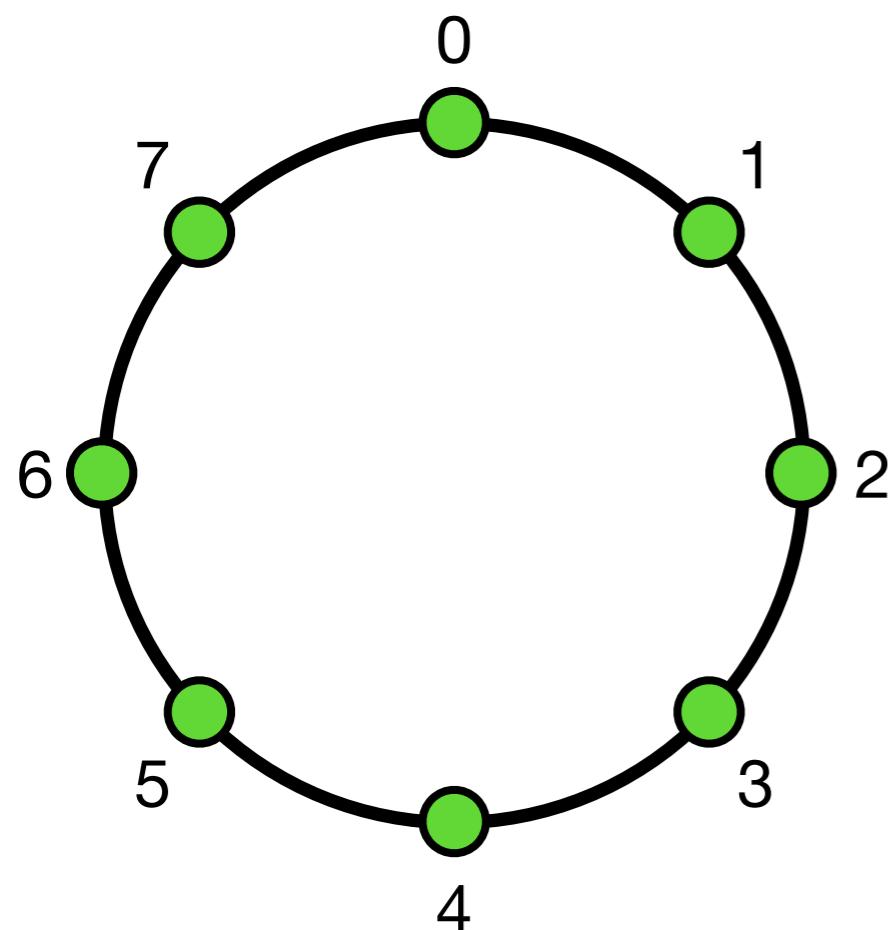
# Wave Number to Frequency

$$= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N)$$

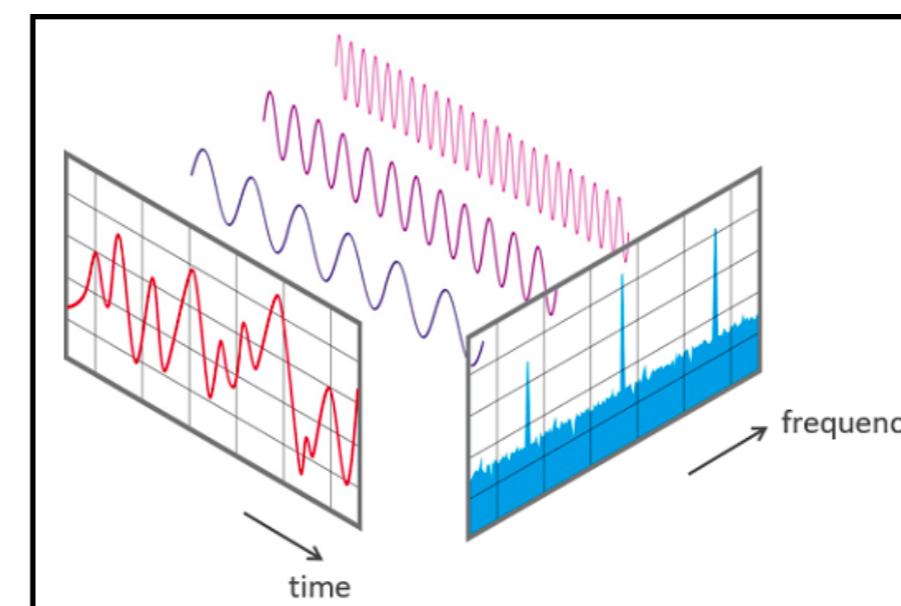
Suppose  $N = 8$

-> k = 0, 1, ... 7

for a given  $k$ ,  $n = 0, 1, \dots, 7$



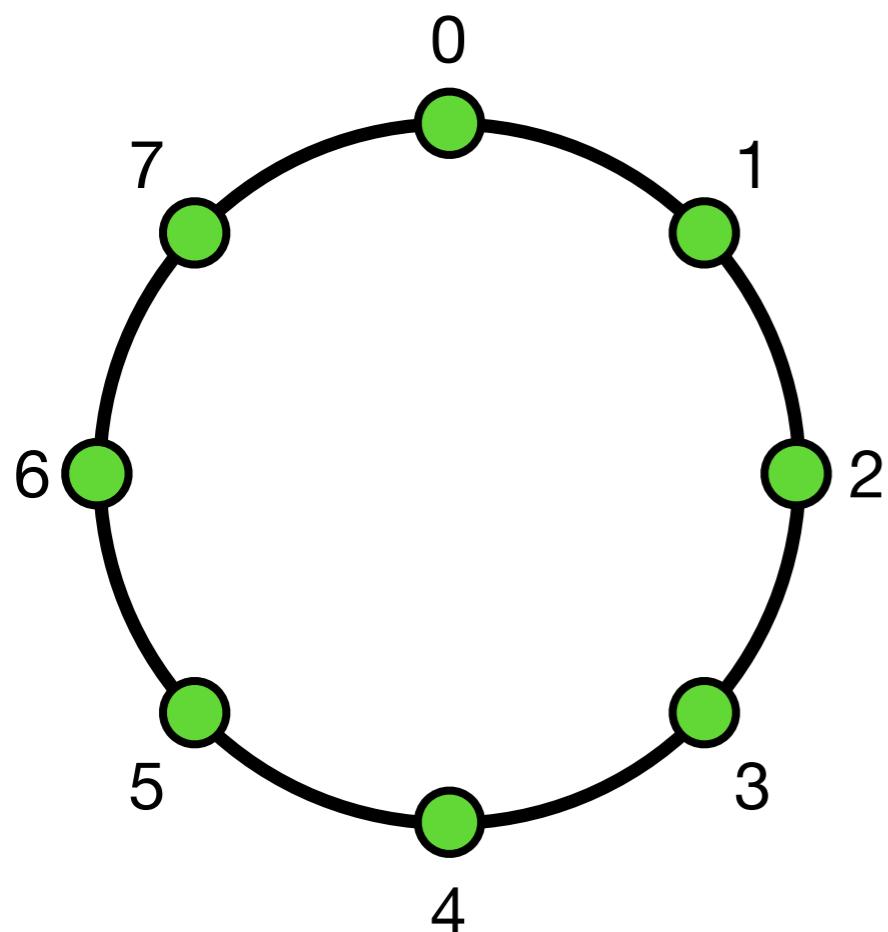
**The Real Question:** What frequency does the wave number  $k$  correspond to in Hz?



# Wave Number to Frequency

At the risk of confusing  
you even more...

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{i2\pi}{N} kn} \\ &= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)] \end{aligned}$$



$$\begin{bmatrix} \mathbf{F1} \\ \mathbf{F2} \\ \mathbf{F3} \\ \mathbf{F4} \\ \mathbf{F5} \\ \mathbf{F6} \\ \mathbf{F7} \\ \mathbf{F8} \end{bmatrix} = \begin{bmatrix} \text{Clocks} \\ \vdots \\ \text{Clocks} \end{bmatrix}^{\text{k}^* n} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \\ f_8 \end{bmatrix}$$

The matrix equation illustrates the relationship between the frequency components  $\mathbf{F}$  and the corresponding clock phases. The left side is a column vector of frequency components  $\mathbf{F}_1$  through  $\mathbf{F}_8$ . The right side shows the product of a transformation matrix (represented by a grid of clock faces) and a column vector of frequencies  $f_1$  through  $f_8$ .



# Wave Number to Frequency

$$= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N)]$$

**The Real Question:** What frequency does the wave number **k** correspond to in Hz?

## Time Domain Variables

---

$dt$  = sampling interval  
 $T$  = signal duration

## Frequency Domain Variables

---

$k$  = wave number  
**df = frequency interval**

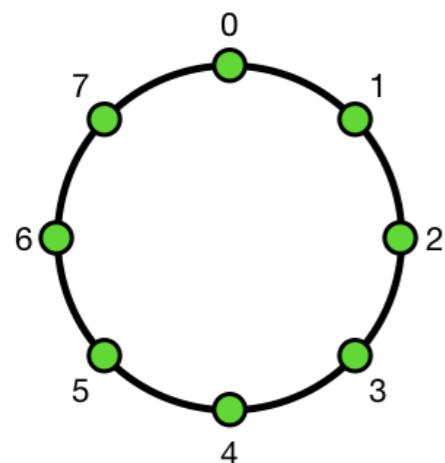
$fs$  = sampling rate  
 $N$  = # of samples / frequencies



# Wave Number to Frequency

$$= \sum_{n=0}^{N-1} x_n \cdot [\cos(2\pi kn/N)]$$

**The Real Question:** What frequency does the wave number  $k$  correspond to in Hz?



wave  $k$  goes around the circle  $k$  times after  $N$  steps ( $k$  cycles)

$N$  steps spans  $T$  seconds

so wave  $k$  goes through  $k$  cycles in  $T$  seconds

what's its frequency?

$$\text{freq}(k) = \frac{k}{T} = \frac{k}{N dt} = \frac{k}{N \frac{1}{fs}} \quad df = \frac{1}{T}$$

max f  
 $= \frac{N-1}{T}$   
next one:  $\frac{N}{T}$   
"fs"



# Wave Number to Frequency

$$freq(k) = \frac{k}{T} = \frac{k}{N dt} = \frac{k}{N \frac{1}{fs}} \quad df = \frac{1}{T}$$

*WvD Chapter 6*

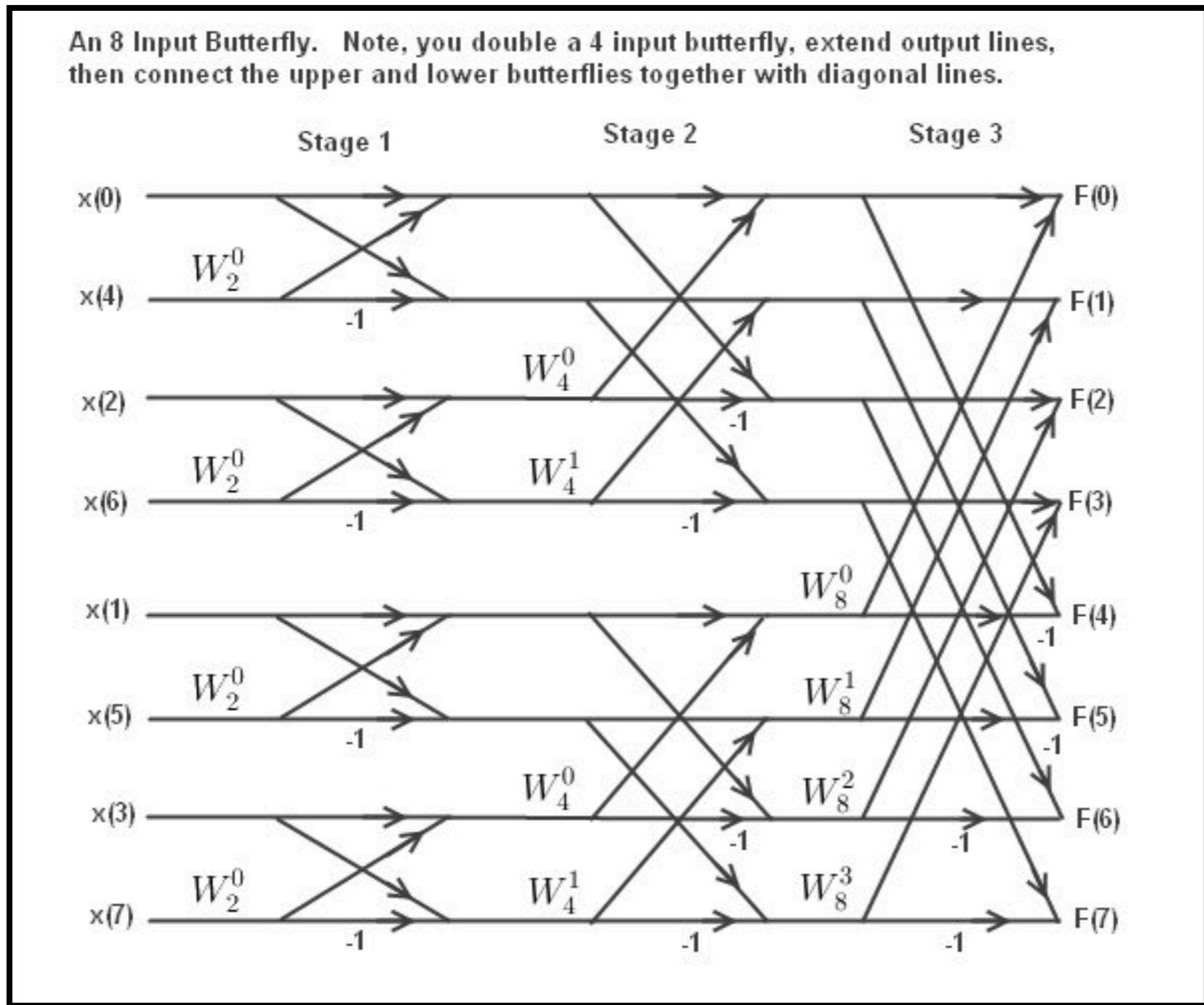
**TABLE E6.4** DFT Time- and Frequency Domain Parameters

$T$ (s)	$s$ (samples/s)	$f_s$	$\Delta f$ (Hz)	$df$	$F$ (Hz)
10	10,000		—	—	—
—	—		1	50	—
—	—		0.5	10	—
5	—		0.2	—	—
5	100		—	—	—
—	1000		—	—	500
—	10,000		1	—	—



# Note on DFT & FFT

**Fast Fourier Transform (FFT)** is a clever algorithm that takes advantage of symmetries and recurrence in the data. It does **not** implement DFT as you do.

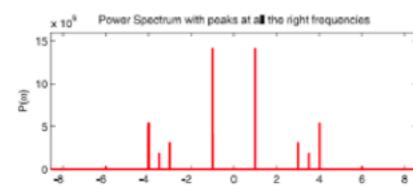


1. Some Fourier properties
2. Computing frequency from wave number
3. Time-frequency analysis



# Time-Frequency Analysis

Can you play a song from knowing its DFT or power spectrum?

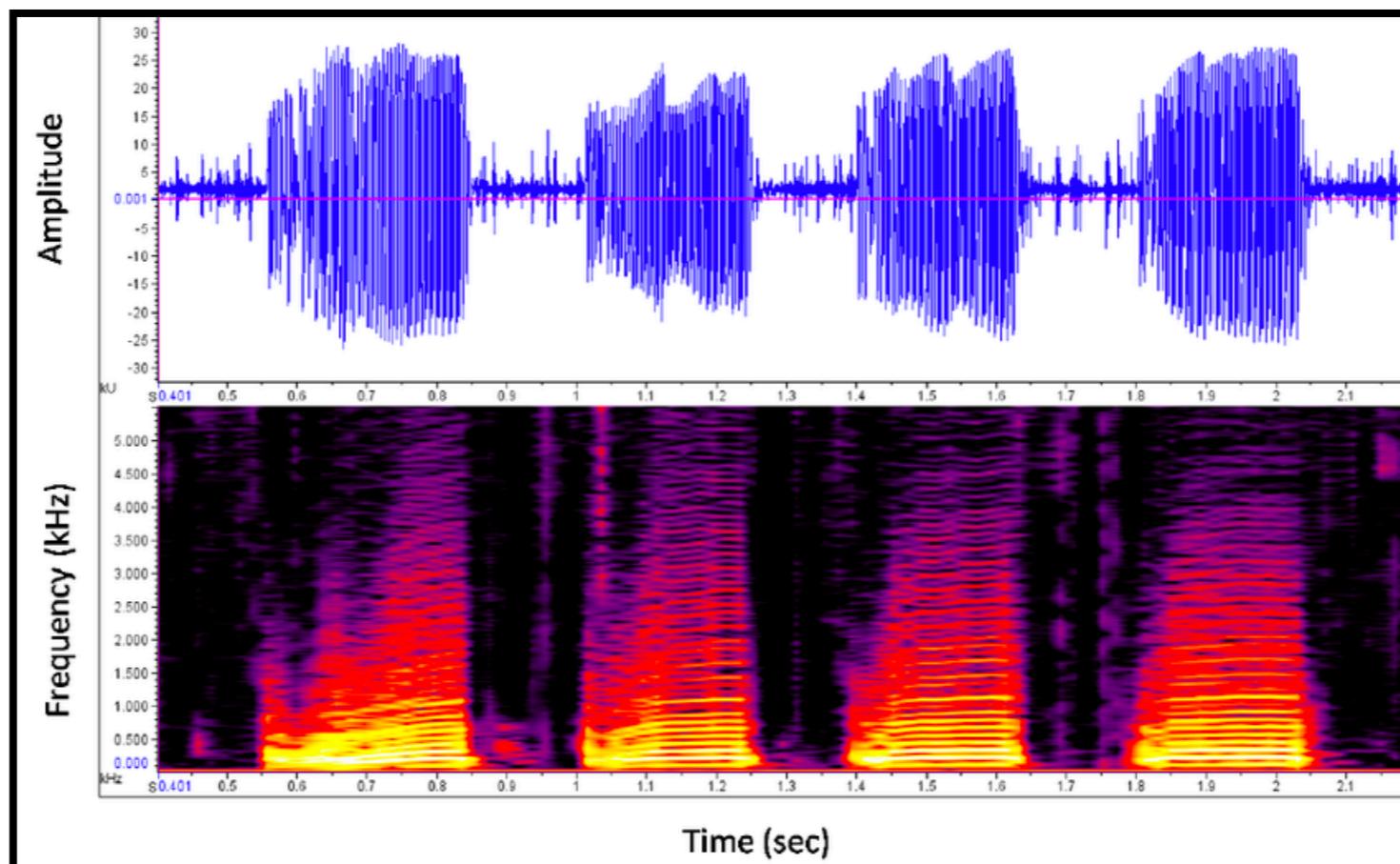


Mary Had a Little Lamb

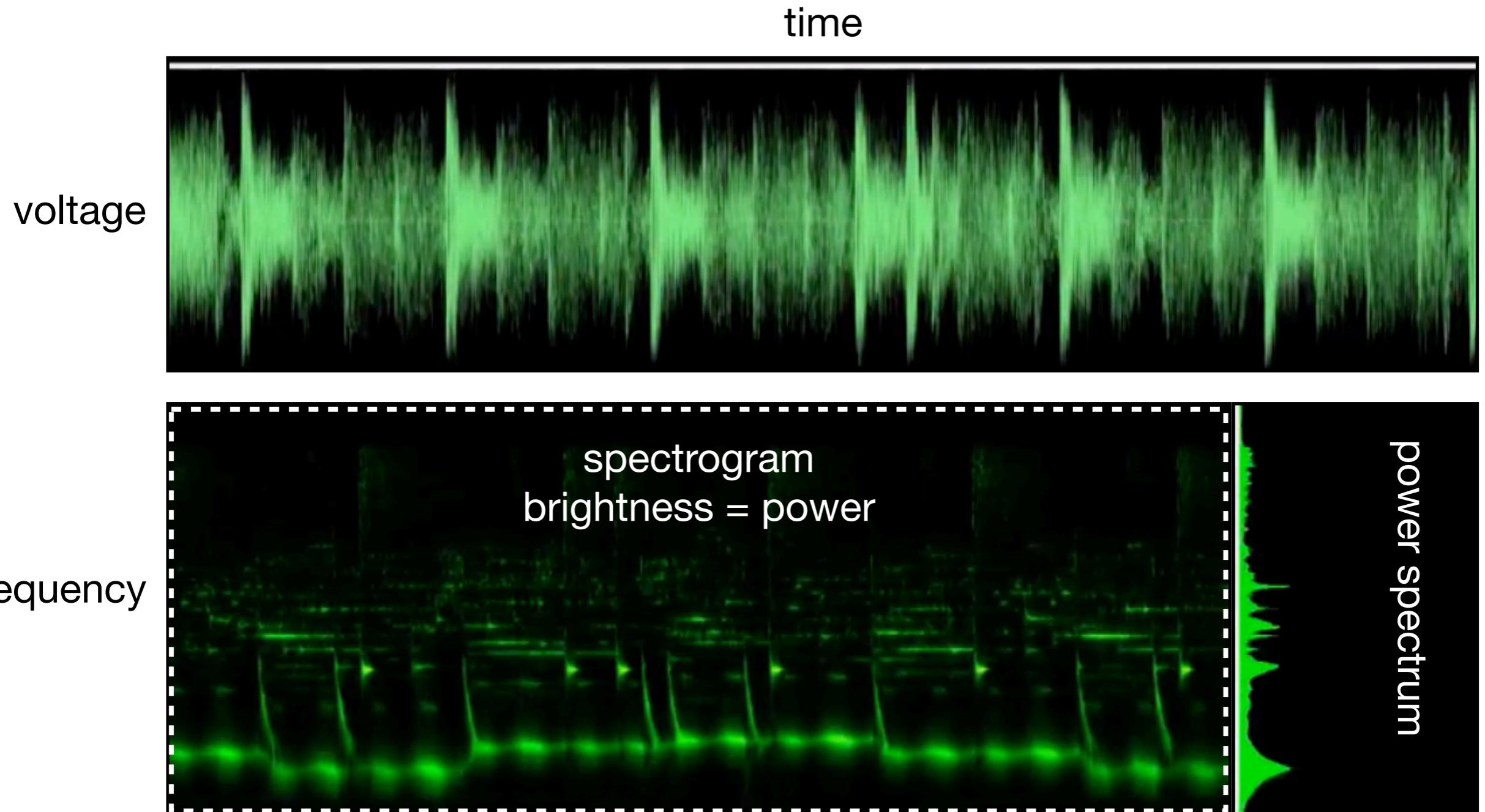
Looking at the DFT or power spectrum is like averaging over all the pictures in a movie, or all the notes in a song.

You know **what notes** are in the song, but not **when** they are played.

We need time-frequency analysis, or **spectrogram**.

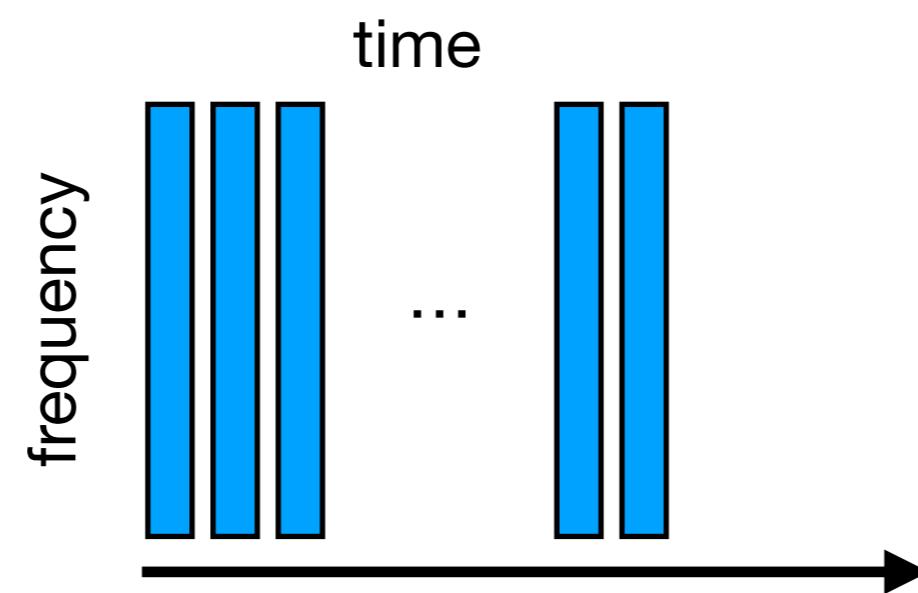
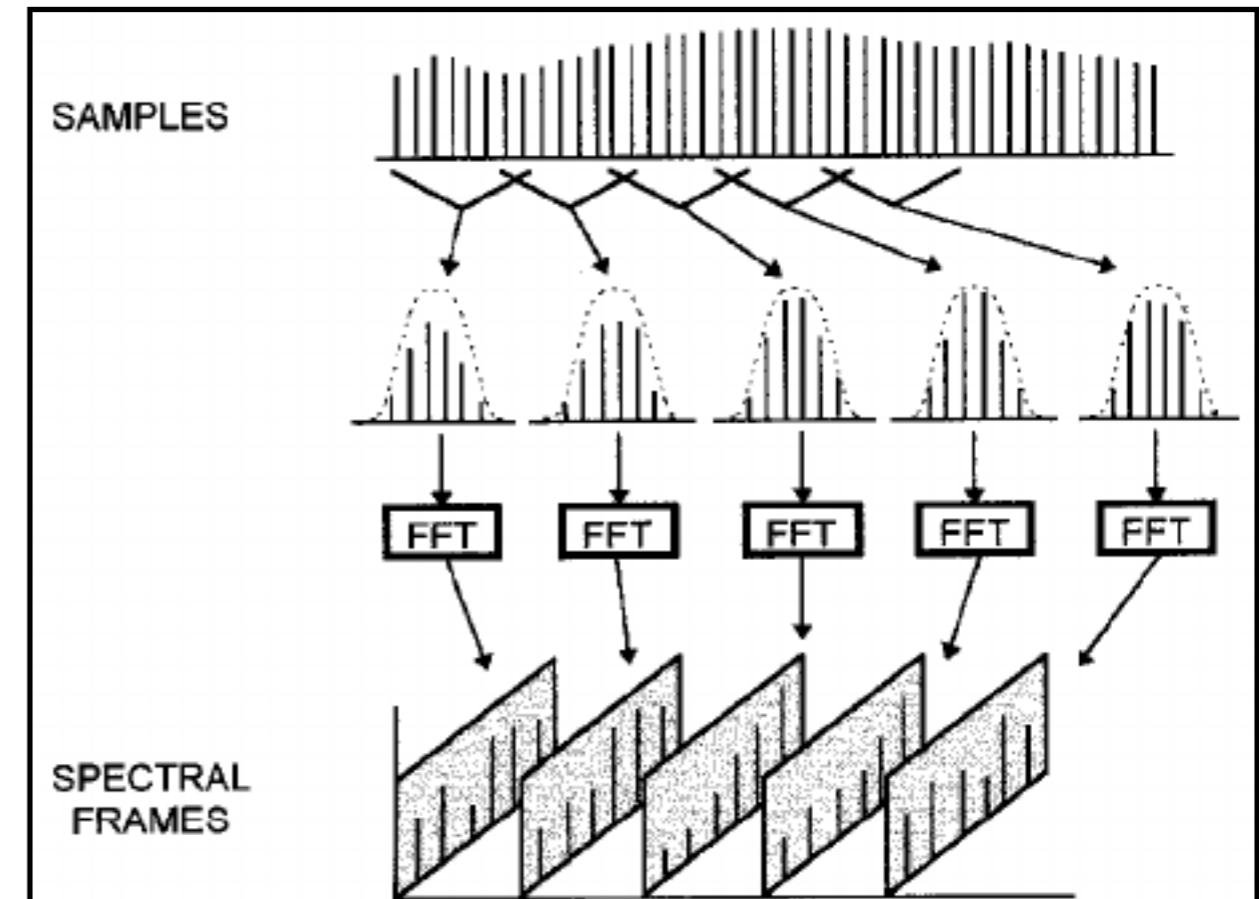
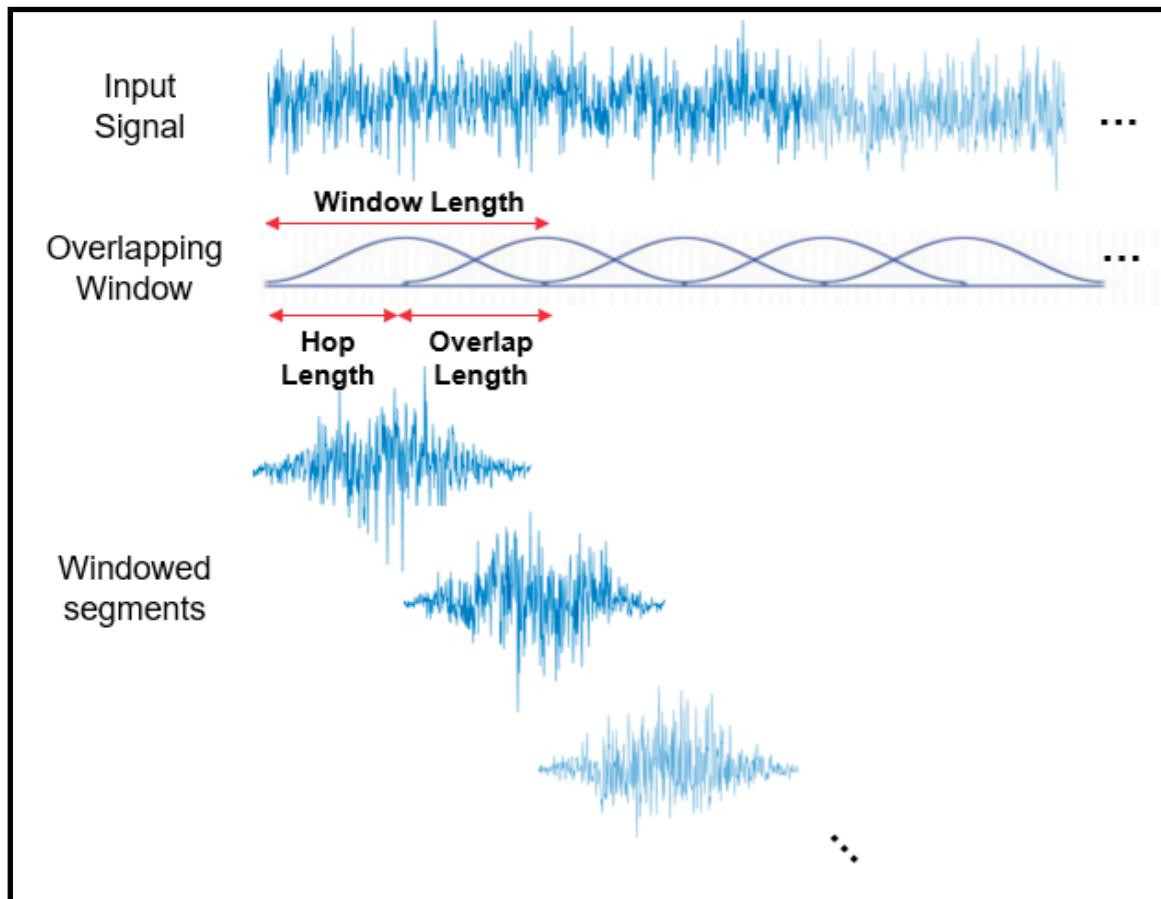


# Time-Frequency Analysis



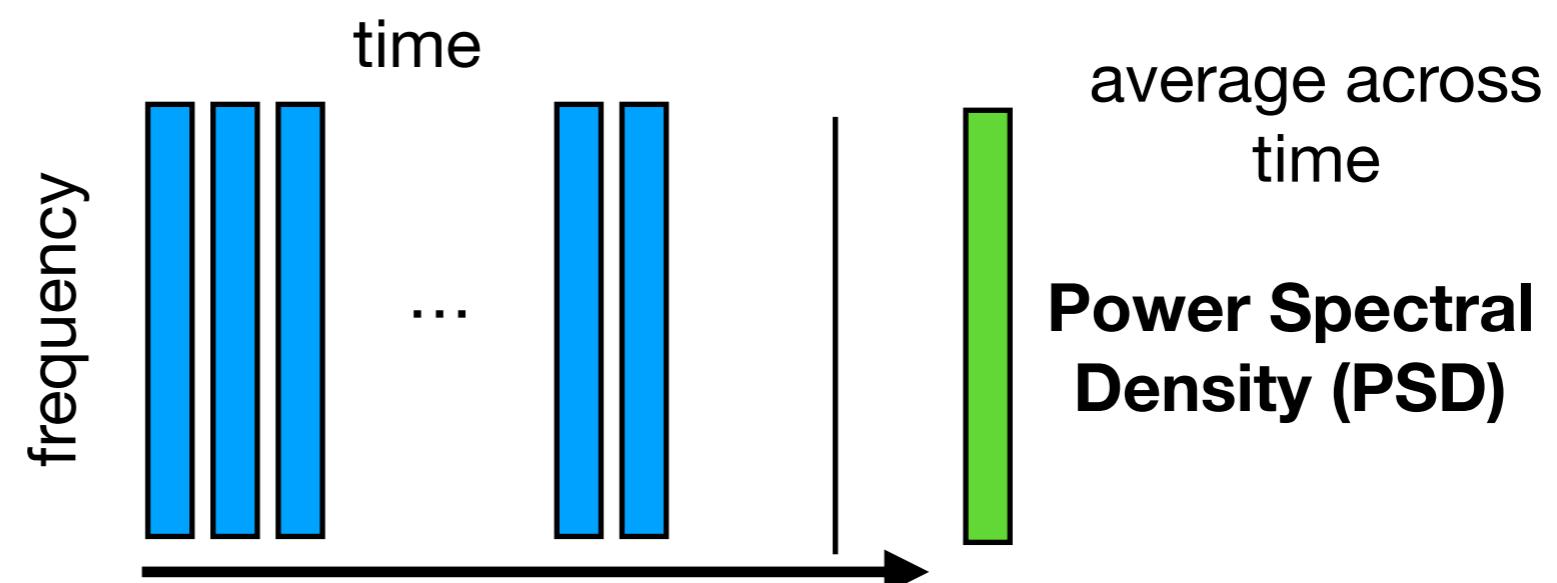
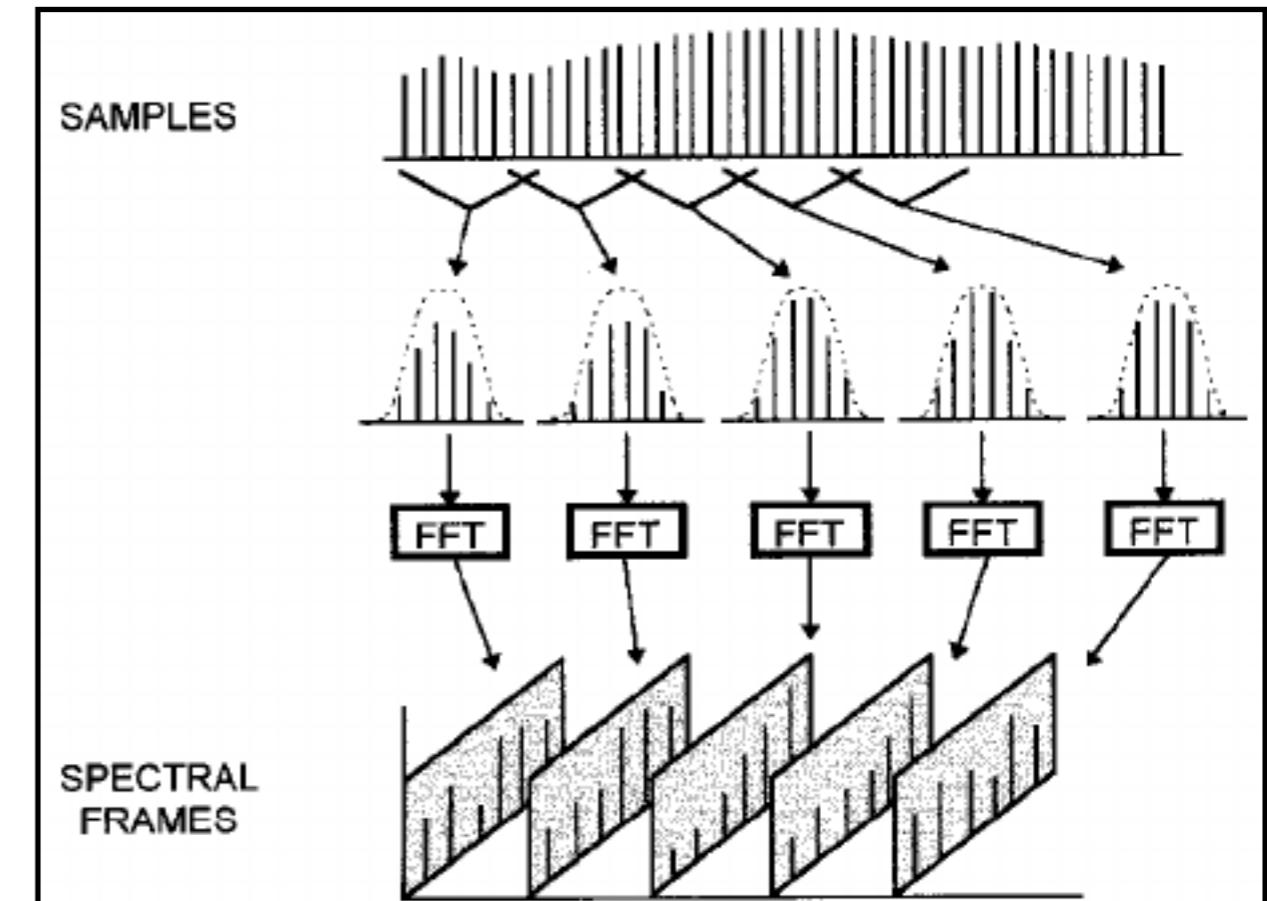
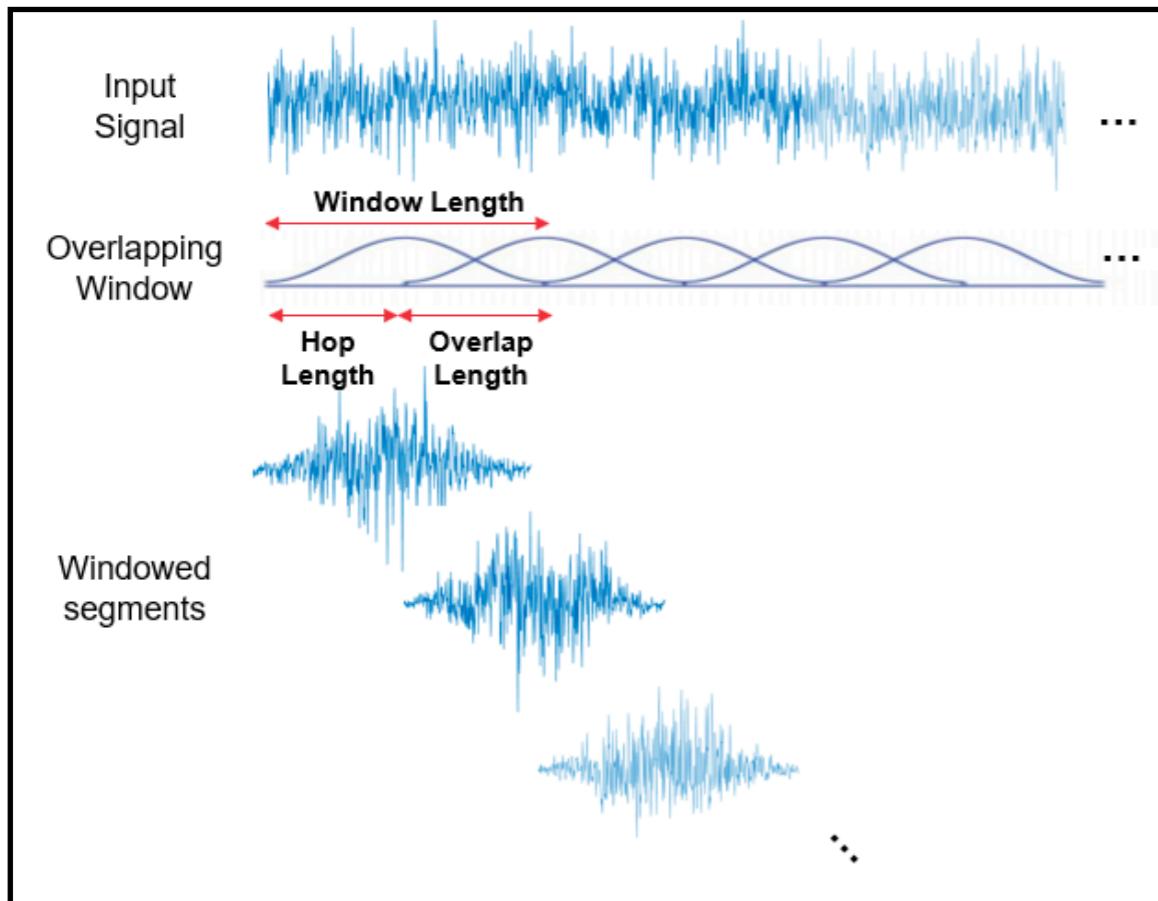
# Sliding Window Analysis

## Short Time Fourier Transform (STFT)



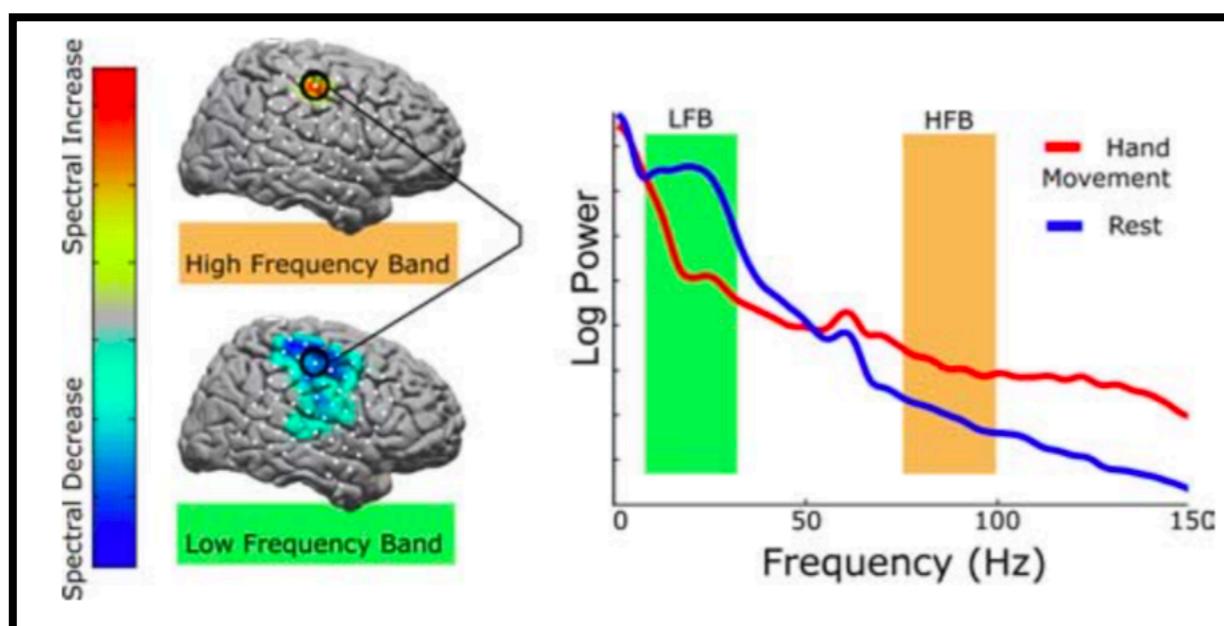
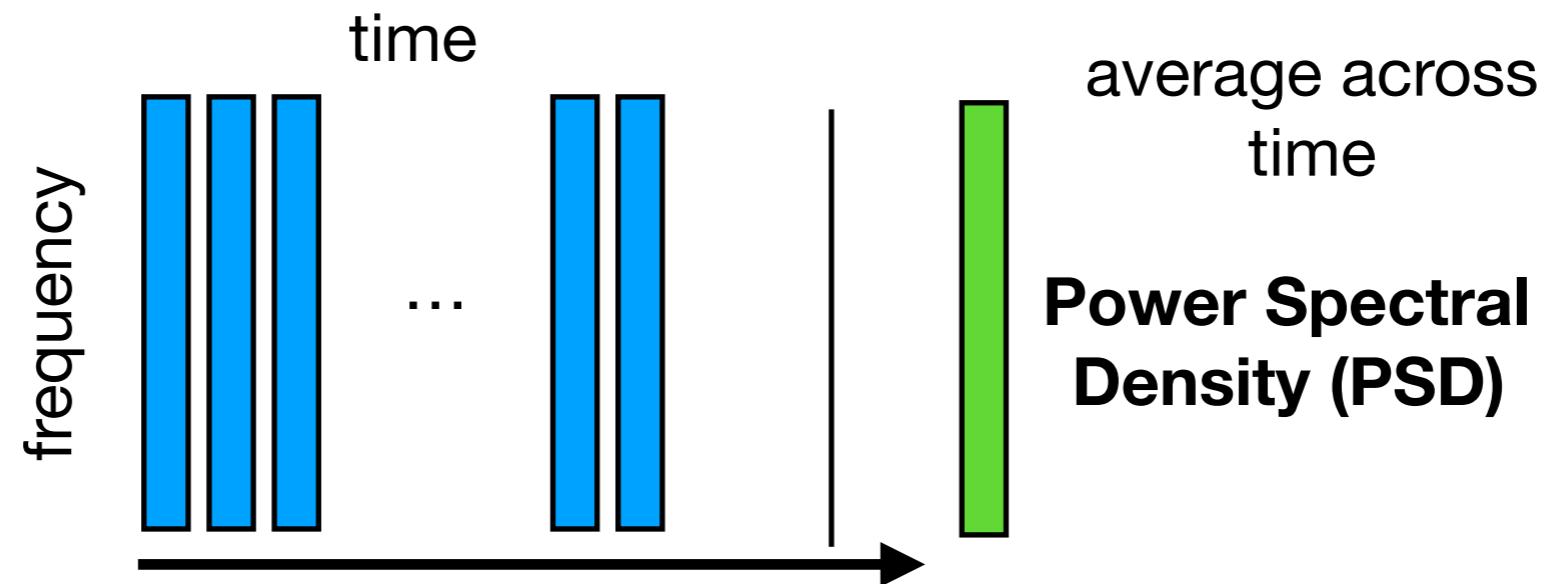
# Power Spectral Density

## Short Time Fourier Transform (STFT)



# Power Spectral Density

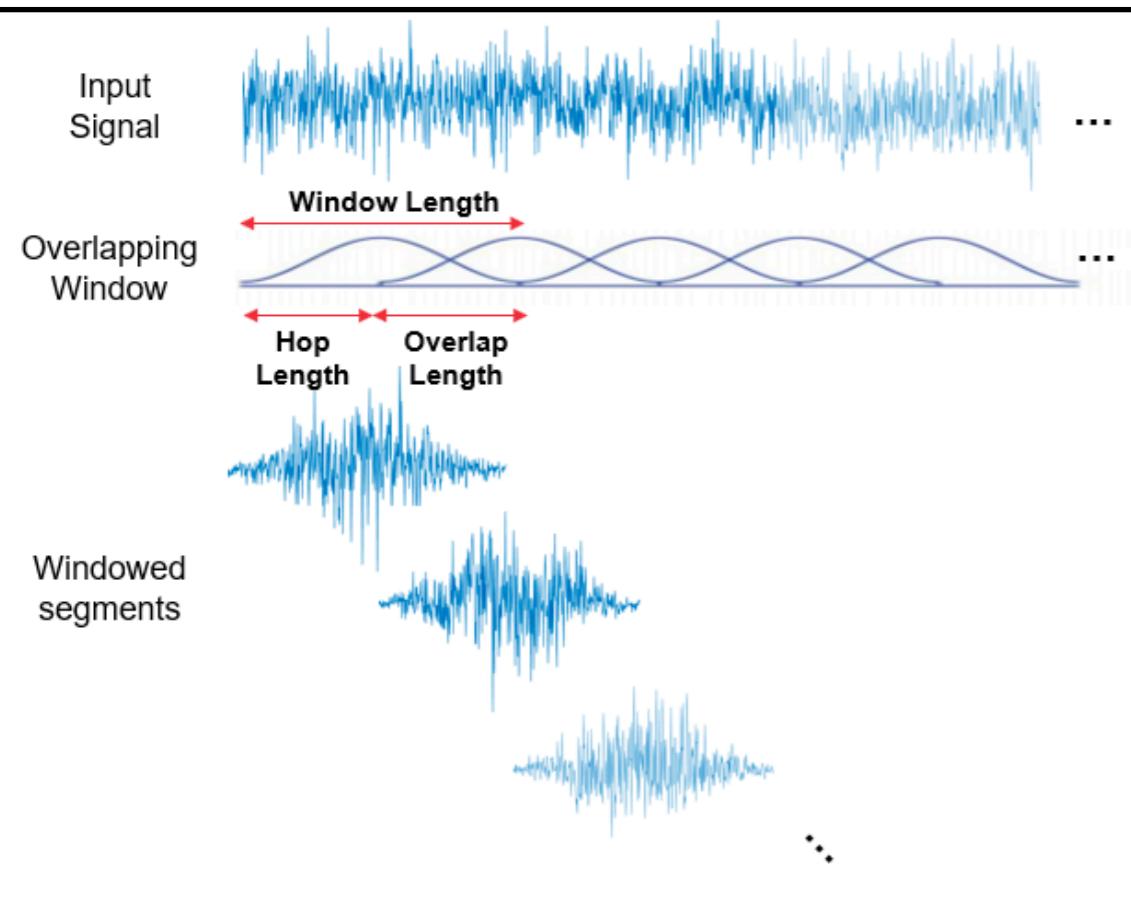
**Welch's (overlapping windows) or  
Bartlet's (non-overlapping windows)  
Method**



Smooth estimate of the power spectrum.



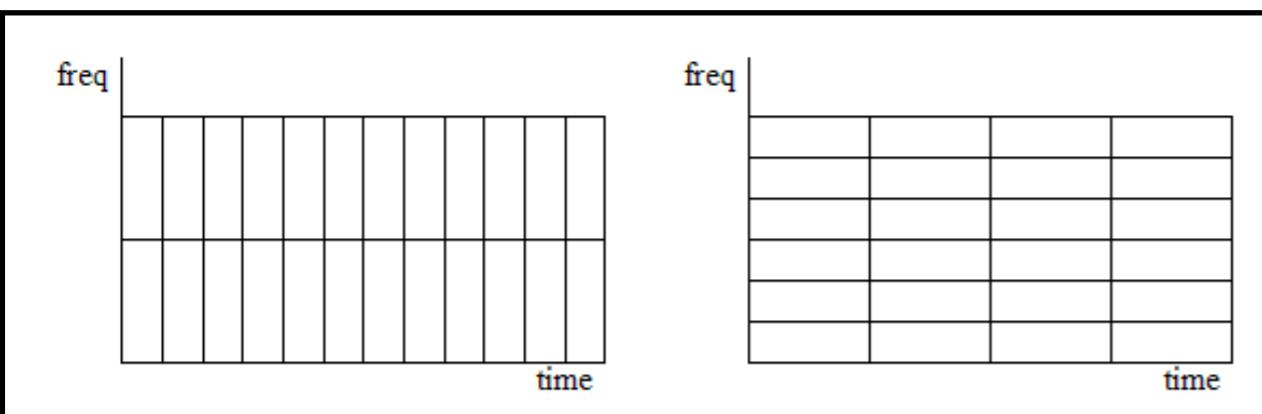
# Time-Frequency Resolution Tradeoff



$$freq(k) = \frac{k}{T} = \frac{k}{N dt} = \frac{k}{N \frac{1}{fs}}$$
$$df = \frac{1}{T}$$

If your data was collected over a total of 60 seconds, and divide it into 12 windows, you can now estimate power every 5 seconds.

But what is your frequency resolution now?



1. Some Fourier properties
2. Computing frequency from wave number
3. Time-frequency analysis

<https://tinyurl.com/cogs118c-att>



1 full sized cheatsheet on plain white (or lined) paper

## **60 min long: before or after reading discussion?**

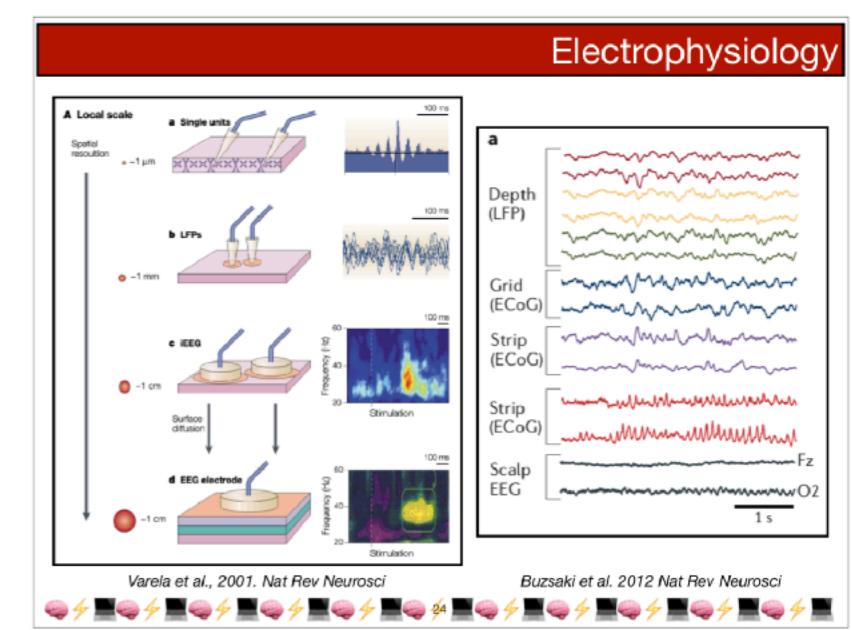
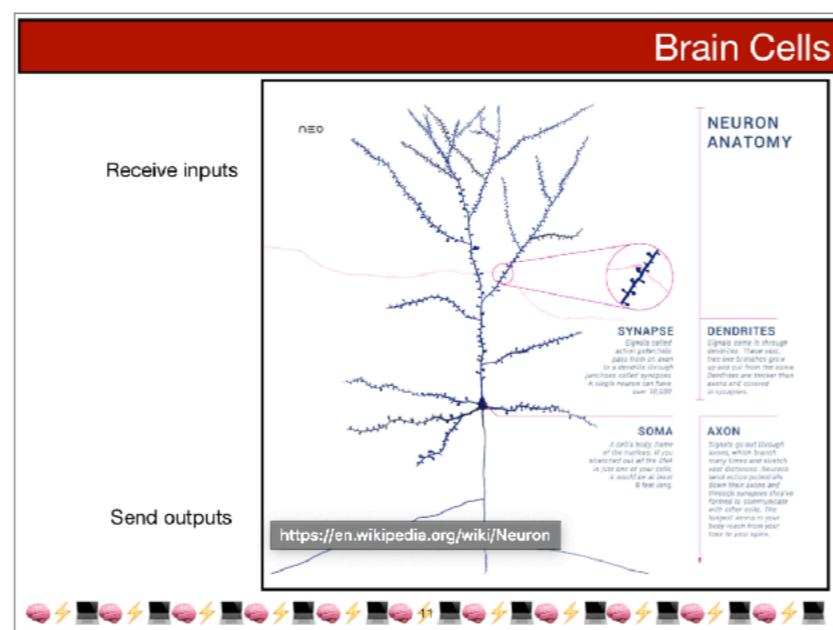
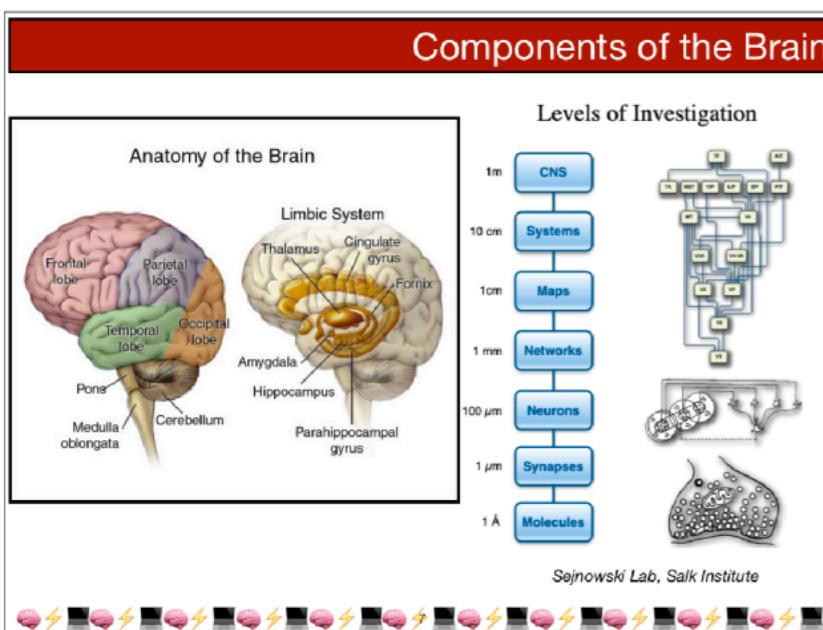
multiple choice, short answers, and math

L2 - L7



## L2 - physiology

Know the stuff on the highlighted slights & notes  
 Anatomy, physiology, spatiotemporal scales of methods  
 Different electrophysiology methods & scales



## L3 - sampling

digitization & sampling

ADC resolution calculations

time resolution & Nyquist rate

## L4 - noise

ERP paradigm + reading!

A1 material

ms, rms, SNR calculations

sources of noise

## L5 - LTI system

LTI properties

simple convolution calculation

definitions (delta, LTI, etc)

## L6 - Fourier

family of FT

A2 material

complex exponential

dot product

wavenumber & frequency

## L7 - Fourier

Fourier properties

time & freq variable calculations

**definitions, calculations applications, & examples**

