

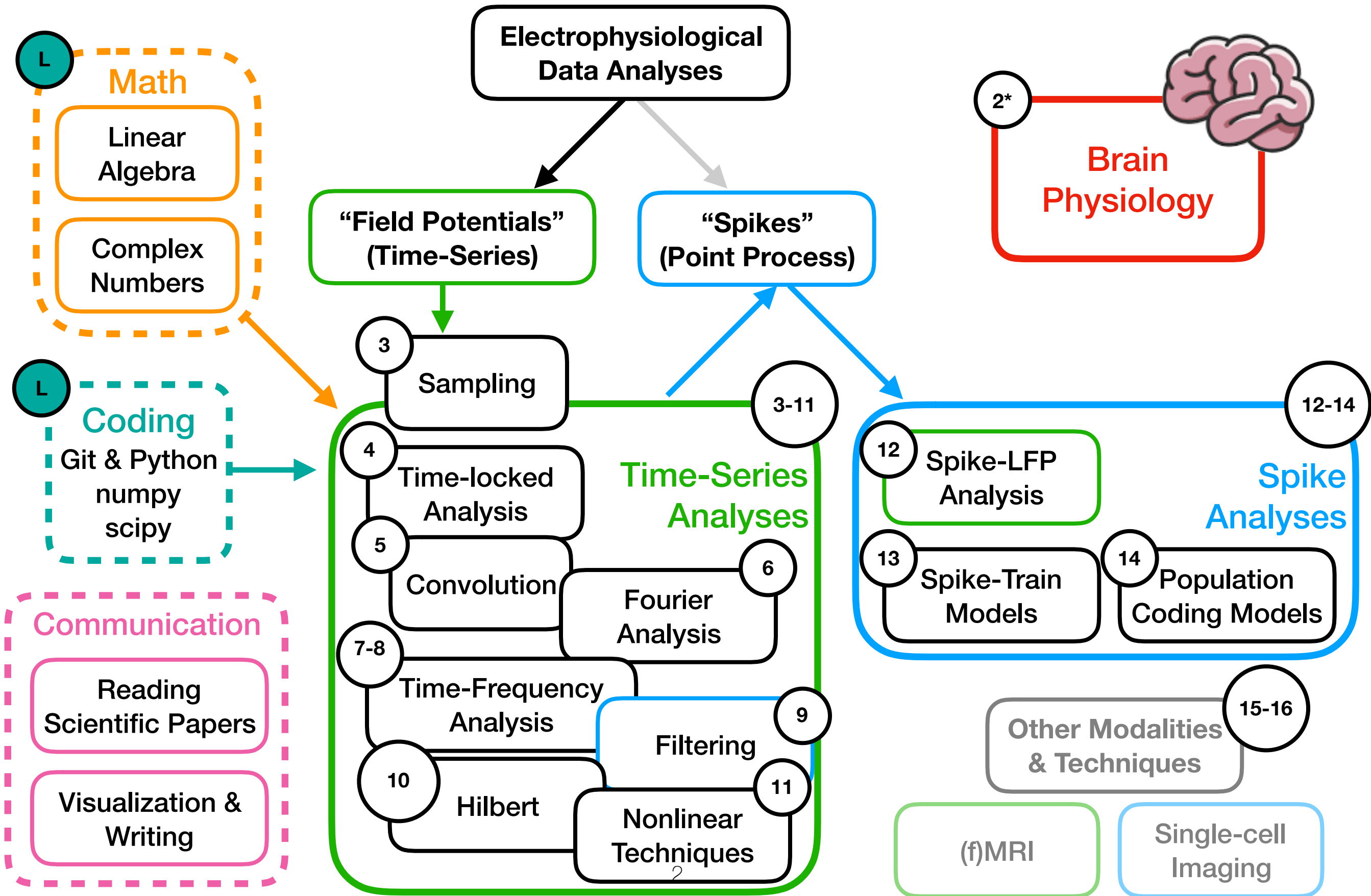
# Analytic Signal & Hilbert Transform

# Lecture 10

## July 18, 2019



# Course Outline: Road Map



1. Motivate “analytic signals”
2. Understand & derive negative frequencies & DFT symmetry
3. Conceptualize Hilbert Transform

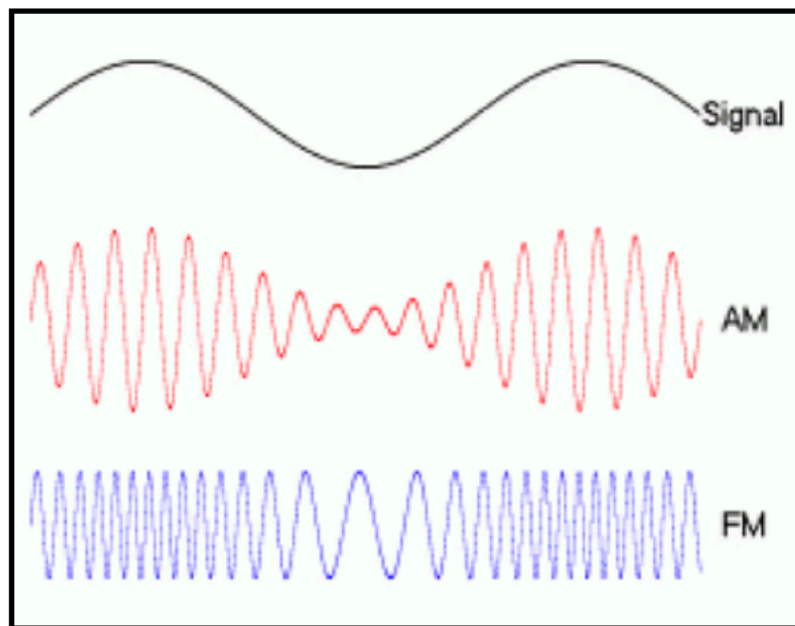


# “Instantaneous” Power and Frequency

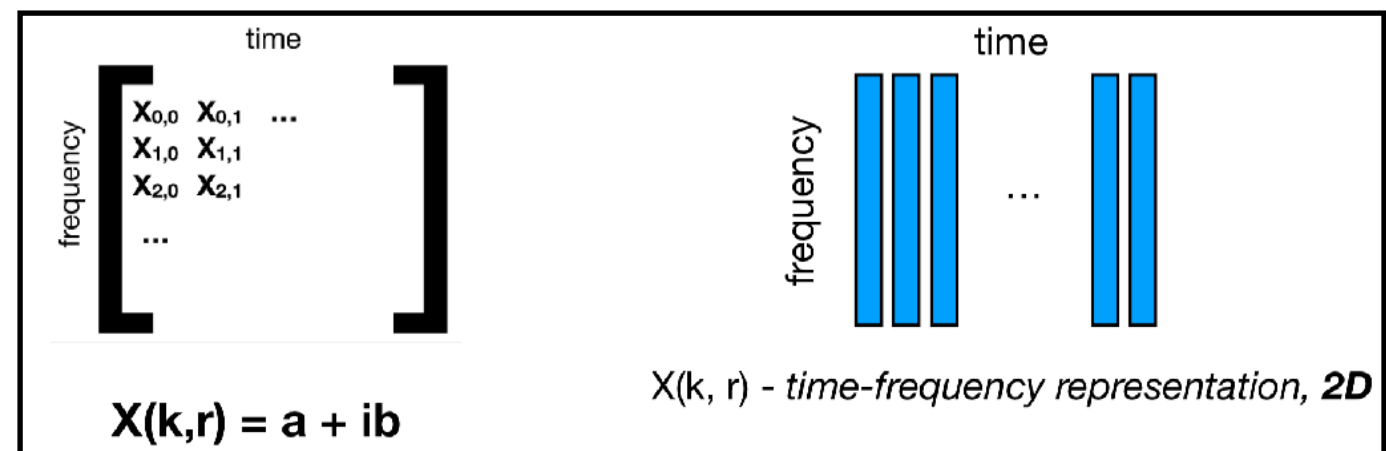
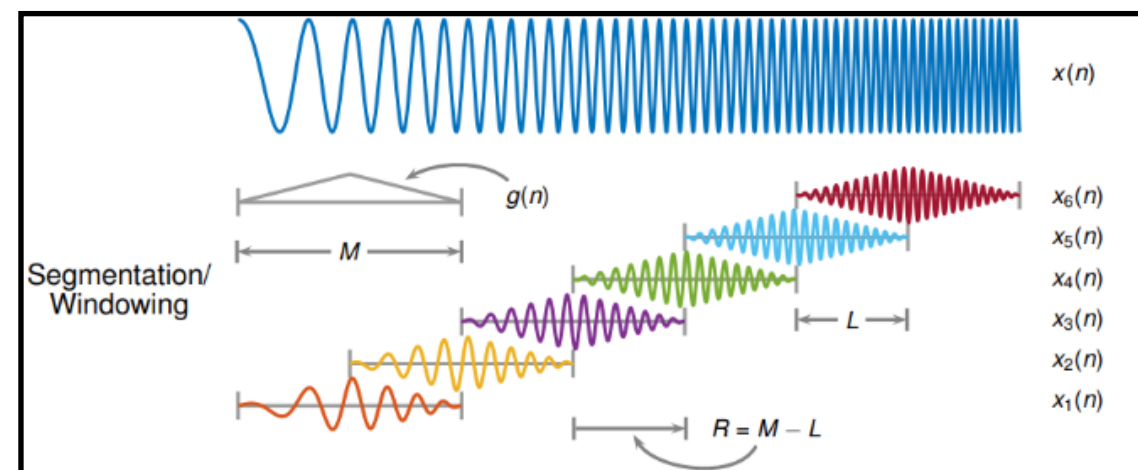
Amplitude (power) and frequency can change very quickly for non-stationary signals like AM & FM radio.

## Frequency modulation

From Wikipedia, the free encyclopedia

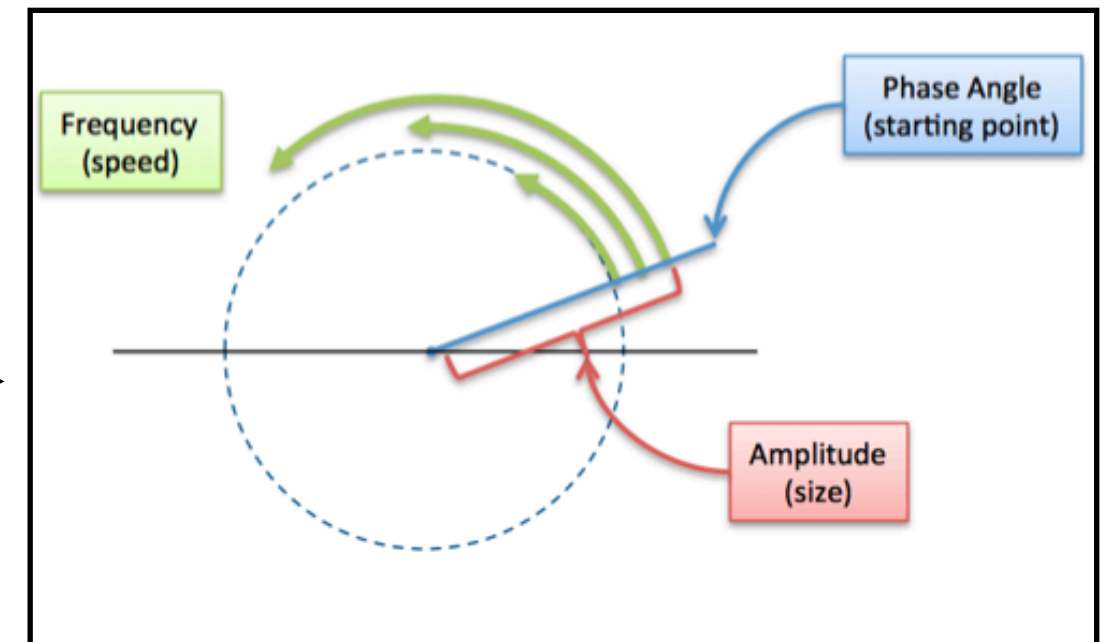
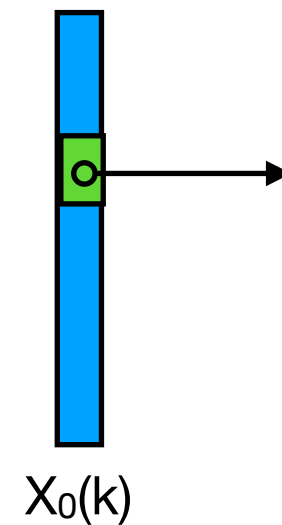
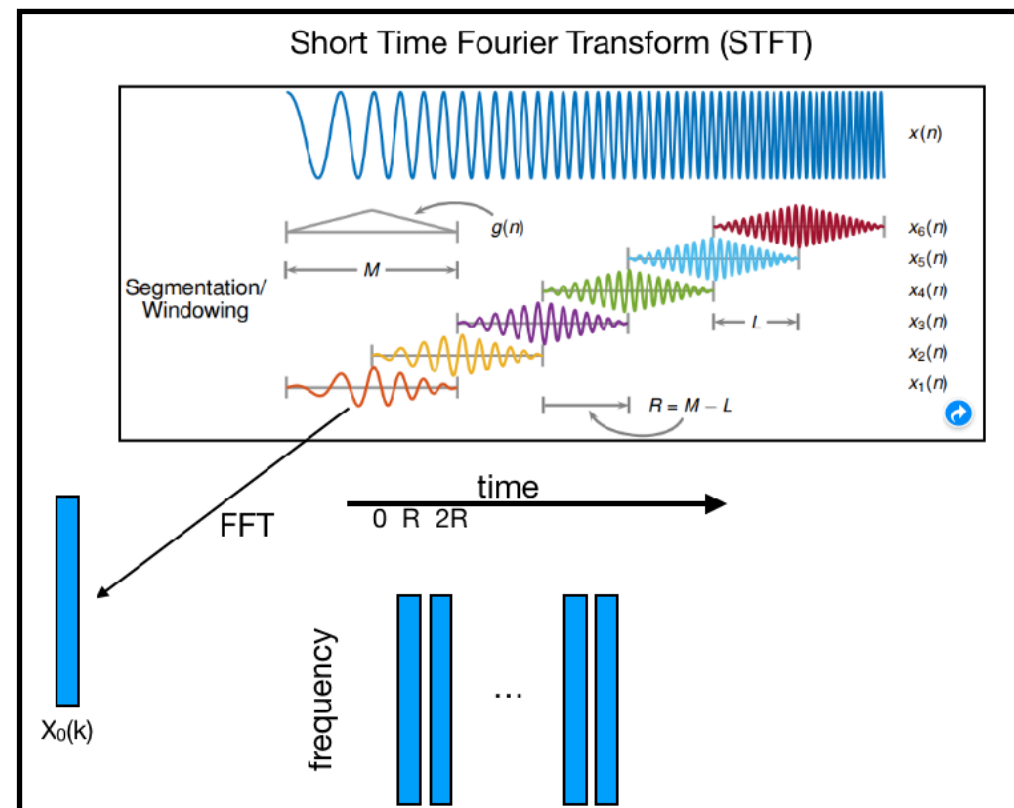


Our proposed solution so far:  
**Time-Frequency Analysis (STFT)**



# “Instantaneous” Power and Frequency

Our proposed solution so far:  
**Time-Frequency Analysis (STFT)**



**average amplitude and phase** of  
data inside the short window

## STFT Parameters (Choice)

**M** = window length (s)

**R** = step length (s)

**L** = overlap length (s)

$$* M = R + L$$

We can only distinguish a frequency resolution of \_\_\_\_\_,  
at a time resolution of \_\_\_\_\_

How can we improve both?



# “Instantaneous” Power and Frequency

How can we improve both?

## STFT Parameters (Choice)

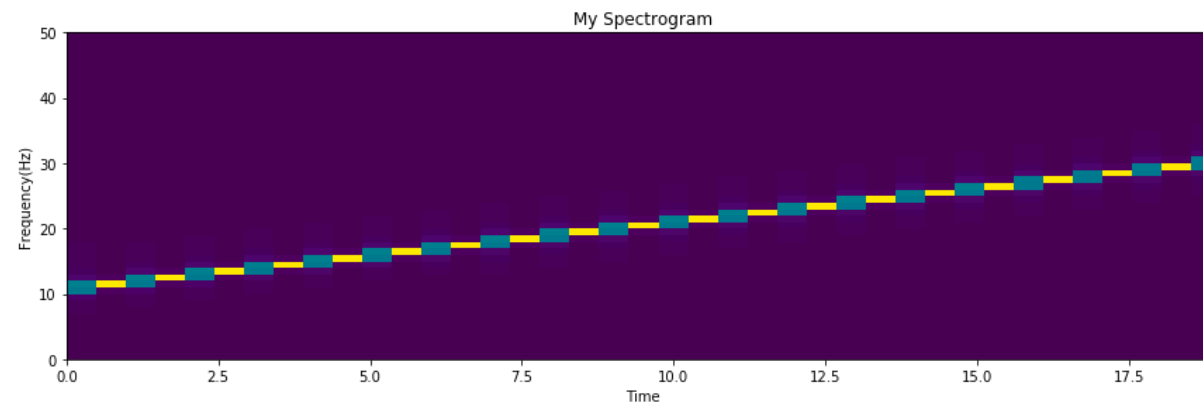
**M** = window length (s)

**R** = step length (s)

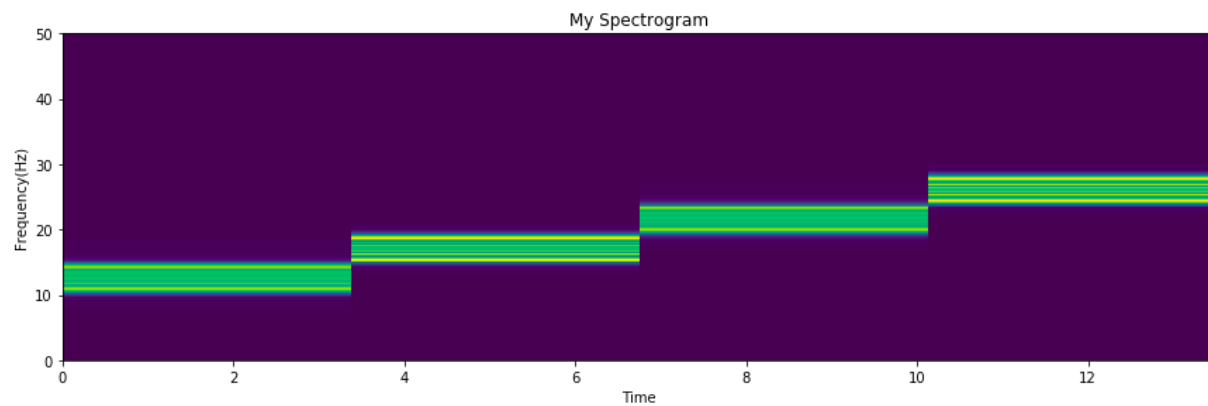
**L** = overlap length (s)

\* **M = R + L**

$M = 1\text{s}, R = 0.5\text{s}$

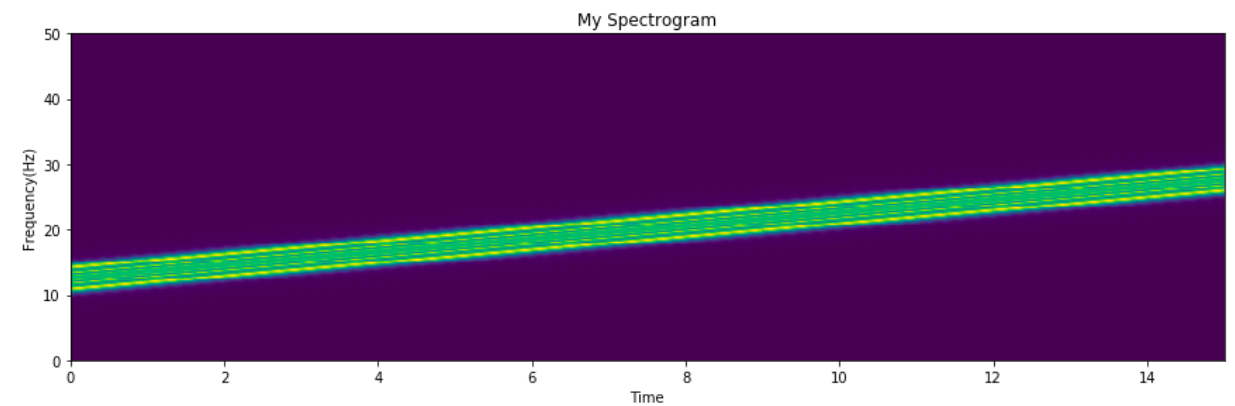


$M = 5\text{s}, R = 0.5\text{s}$



**Increase M:** better frequency resolution

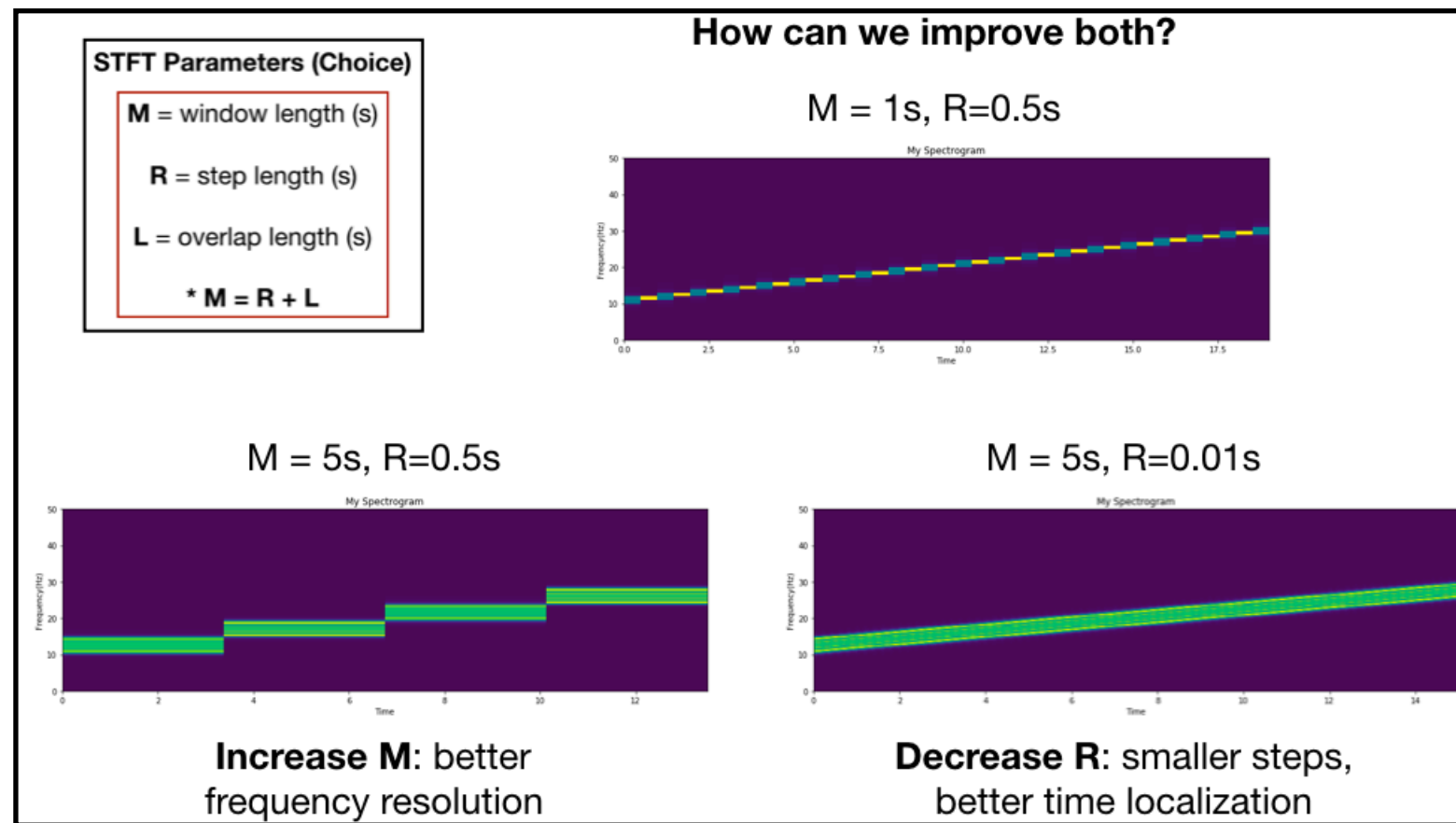
$M = 5\text{s}, R = 0.01\text{s}$



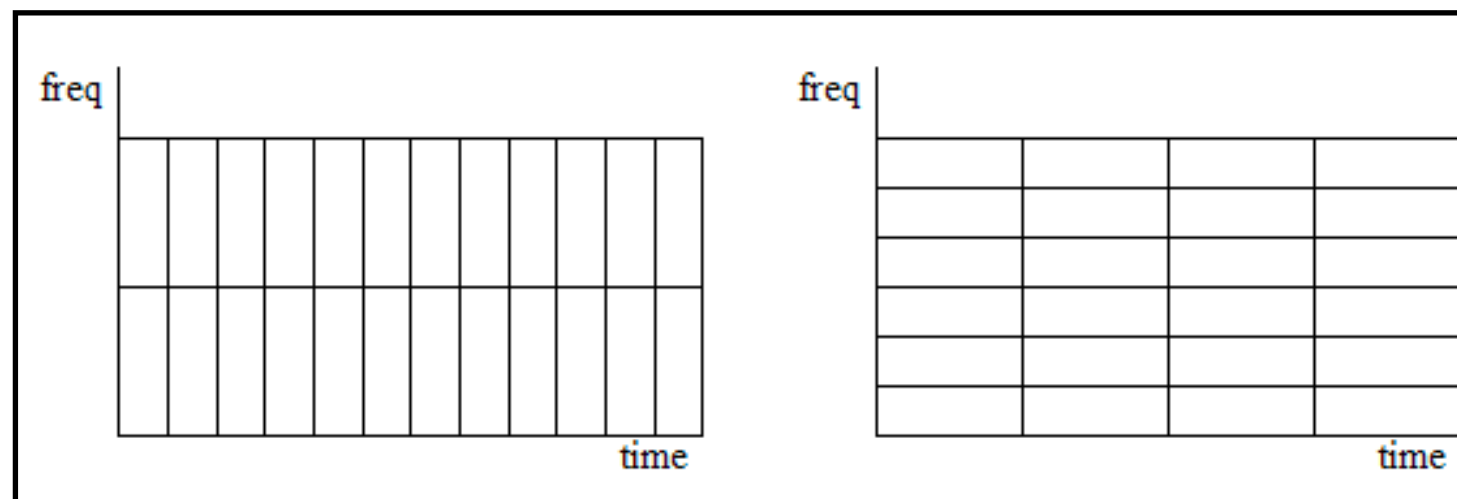
**Decrease R:** smaller steps, better time localization



# “Instantaneous” Power and Frequency



But there is a limit on both, and it's a huge waste.



# In the Brain: Neural Signals

**Neural oscillations are never stationary:**  
power and frequency change very quickly.

nature  
COMMUNICATIONS

Article | OPEN | Published: 12 December 2017

Fluctuations in instantaneous frequency predict alpha amplitude during visual perception

Stephanie Nelli , Sirawaj Itthipuripat, Ramesh Srinivasan & John T. Serences 

## Frequency modulation of neural oscillations according to visual task demands

Andreas Wutz, David Melcher, and Jason Samaha

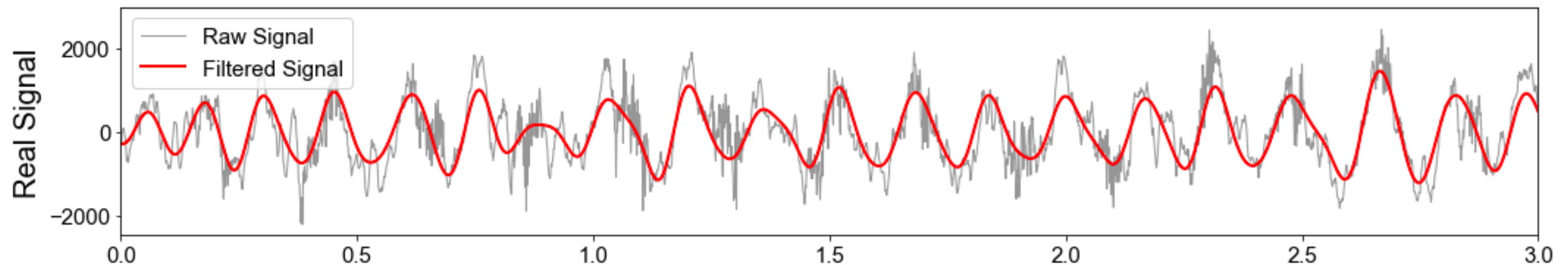


## Fluctuations in Oscillation Frequency Control Spike Timing and Coordinate Neural Networks

Michael X Cohen

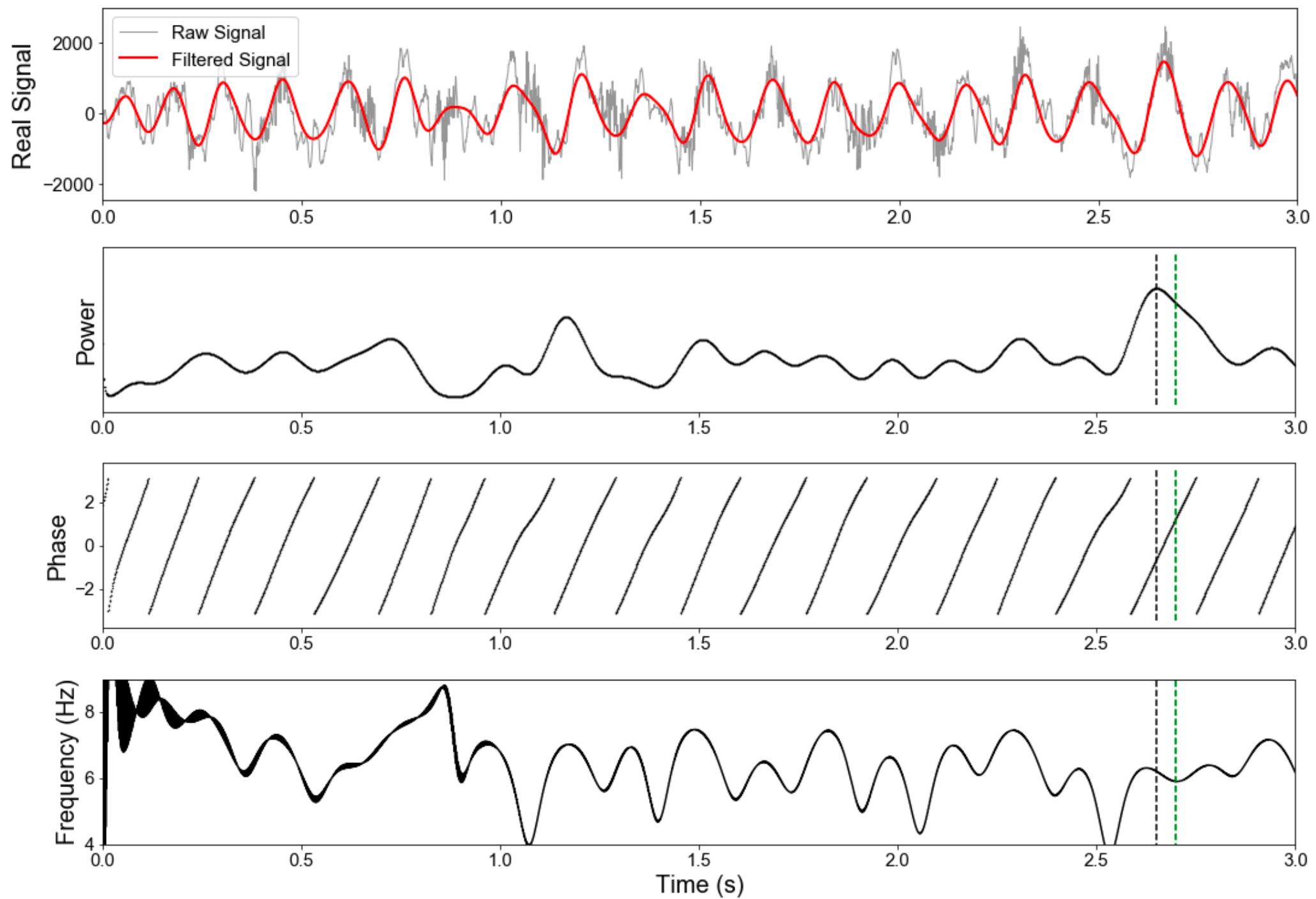
Journal of Neuroscience 2 July 2014, 34 (27) 8988-8998; DOI: <https://doi.org/10.1523/JNEUROSCI.0261-14.2014>

rat hippocampus





# In Neural Signals

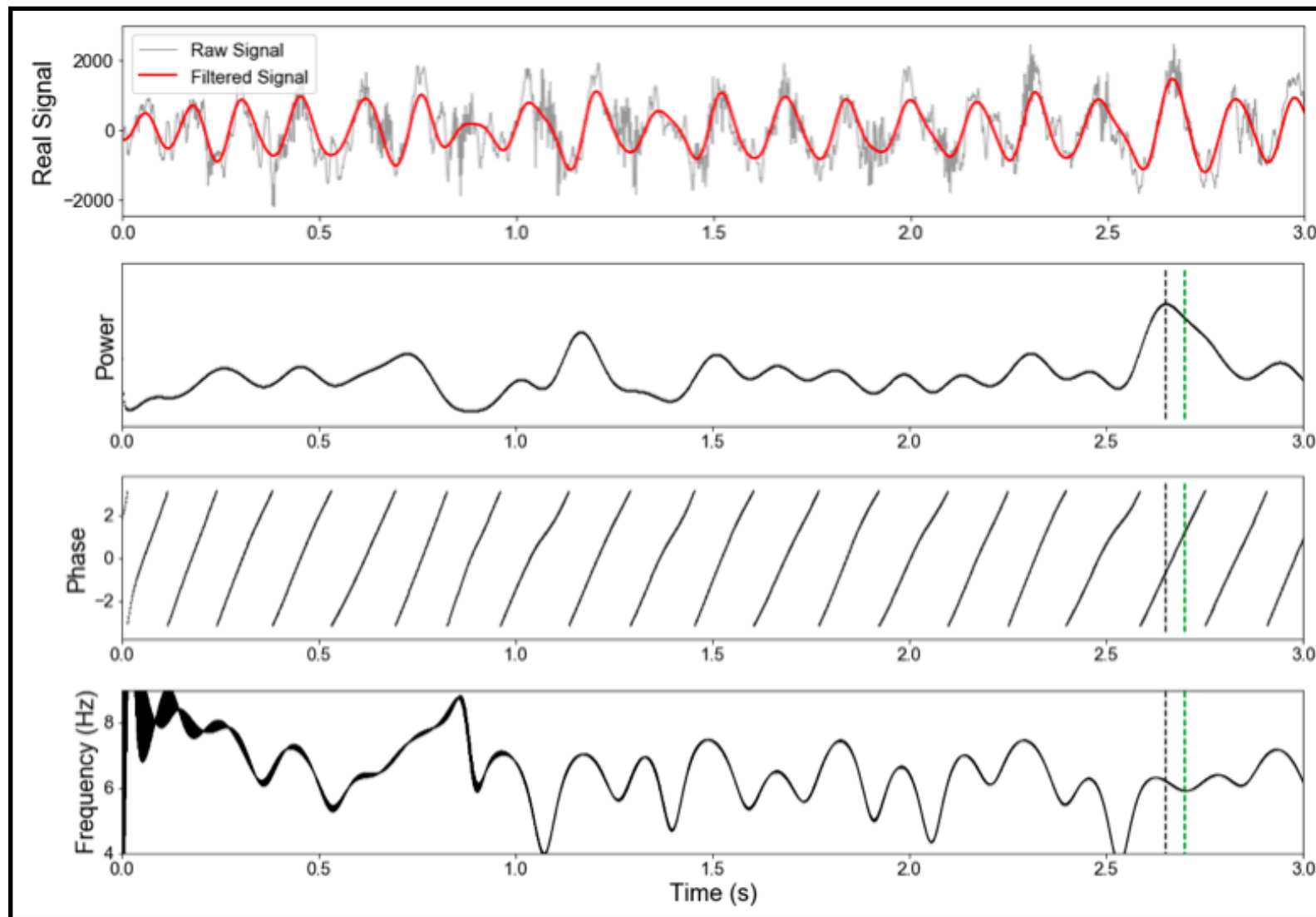


*instantaneous frequency*  $\Phi$ : derivative  
of phase  $\theta$  (rate of phase change)

$$\phi(t) = \frac{d\theta(t)}{dt}.$$



# How to Define/Compute?

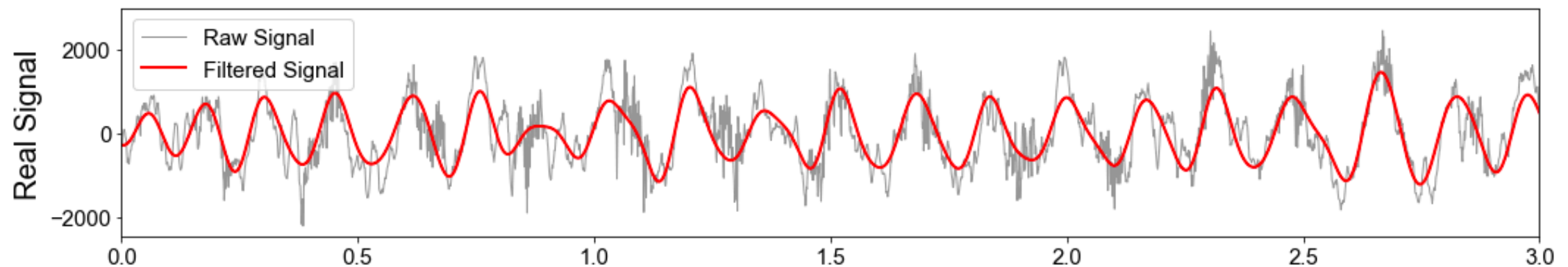


How do we actually compute these quantities?

What are their definitions?



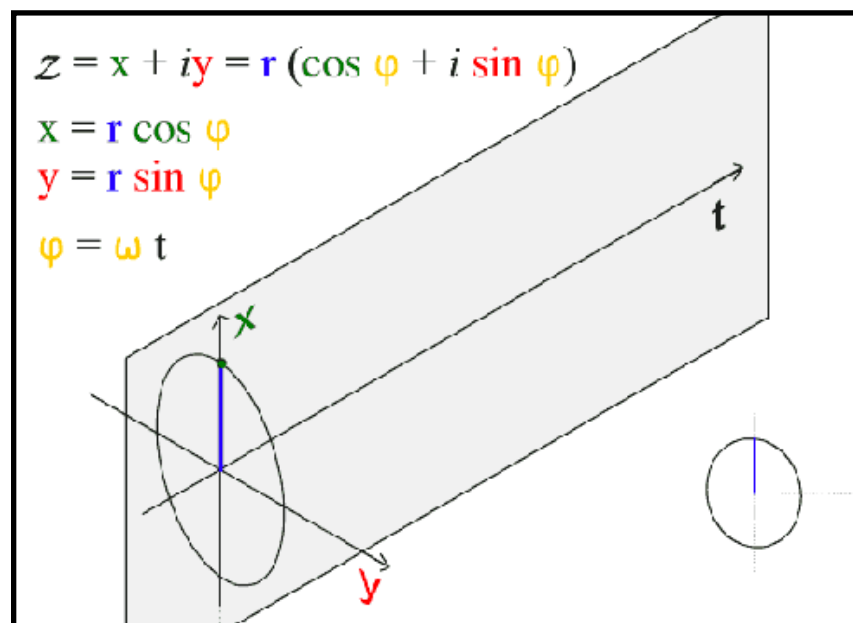
# Analytic Signal



This real-valued signal does not have defined **instantaneous measures**.

Intuition: if I gave you a single time point, can you know its amplitude & phase?

*Amplitude & phase both change, so you need 2 pieces of information (numbers)*



**Analytic Signal: Complex Time-Series**

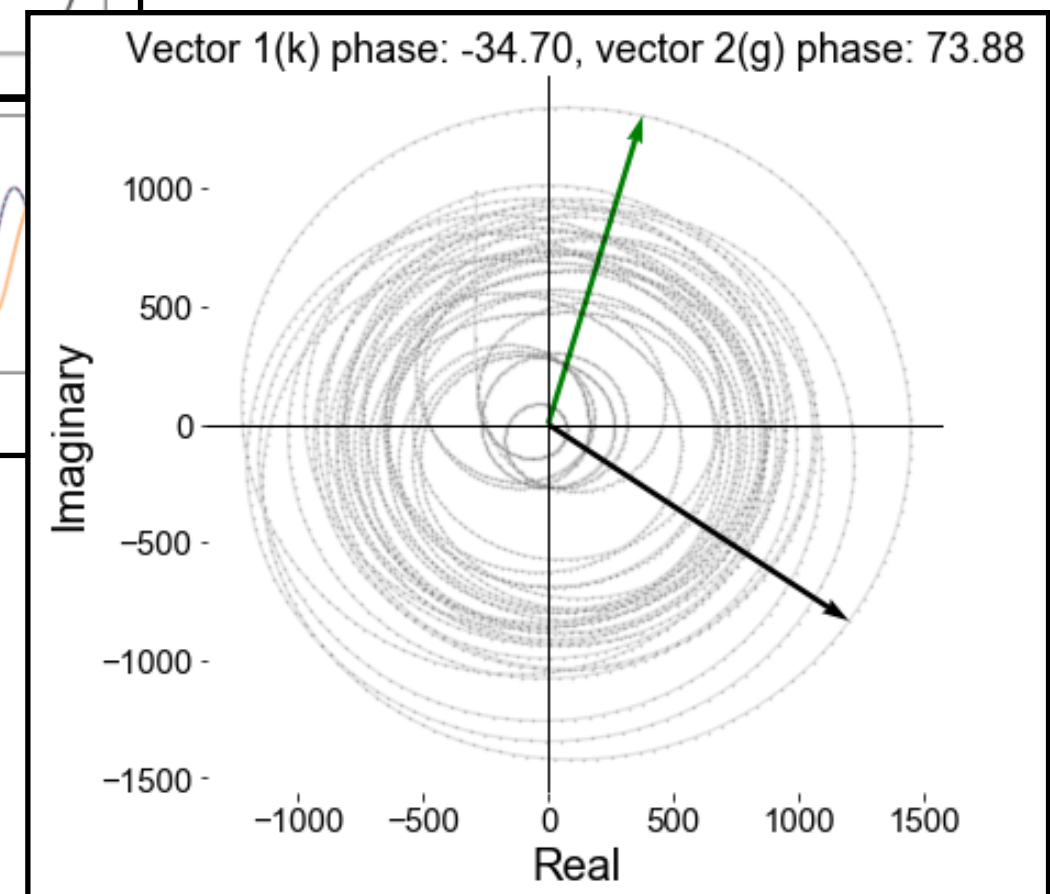
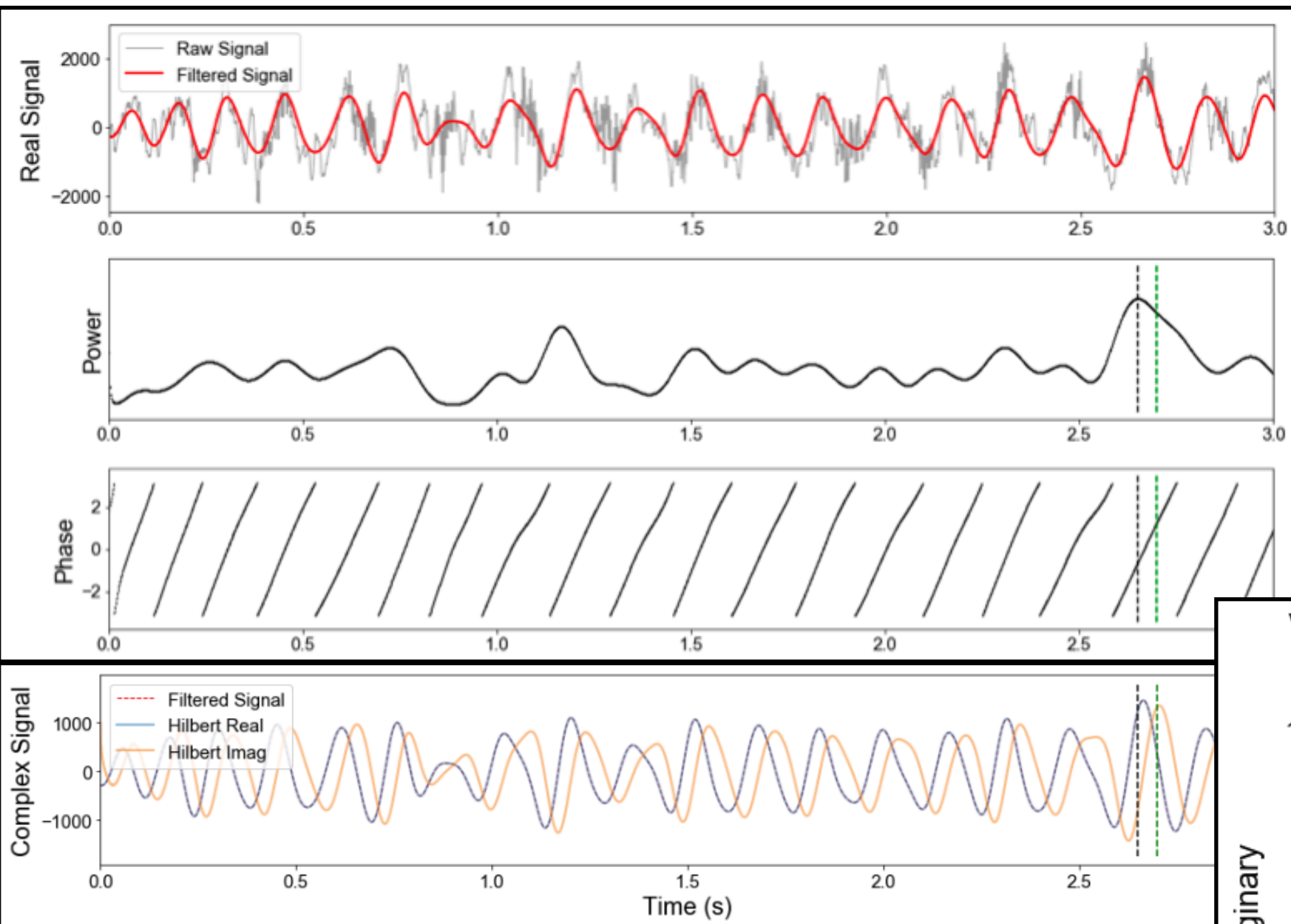
Has well-defined instantaneous time-varying amplitude and phase (and rate of phase change)

**Amplitude:** magnitude

**Phase:** angle



# How to Define/Compute?



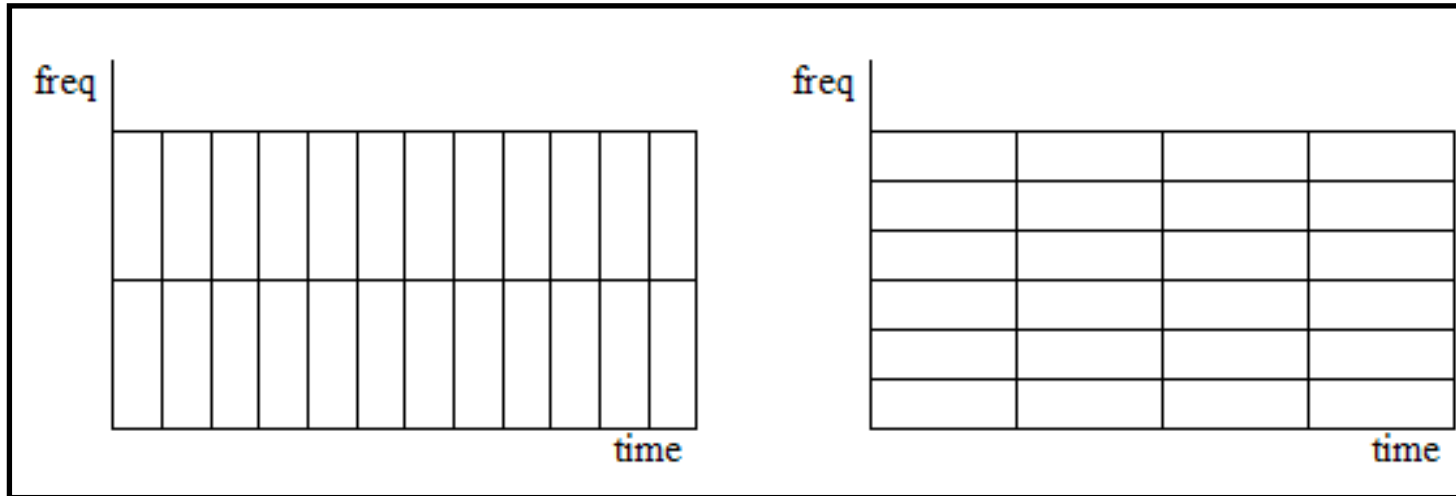
## Analytic Signal: Complex Time-Series

Has well-defined instantaneous time-varying amplitude and phase (and rate of phase change)

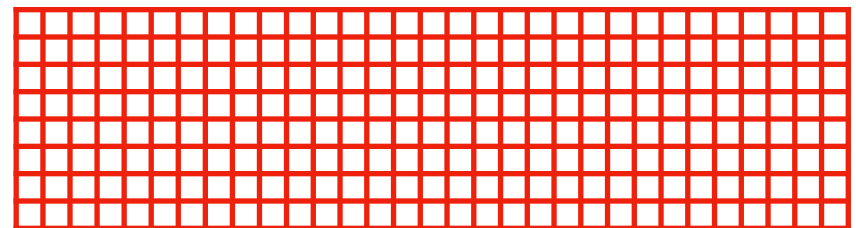
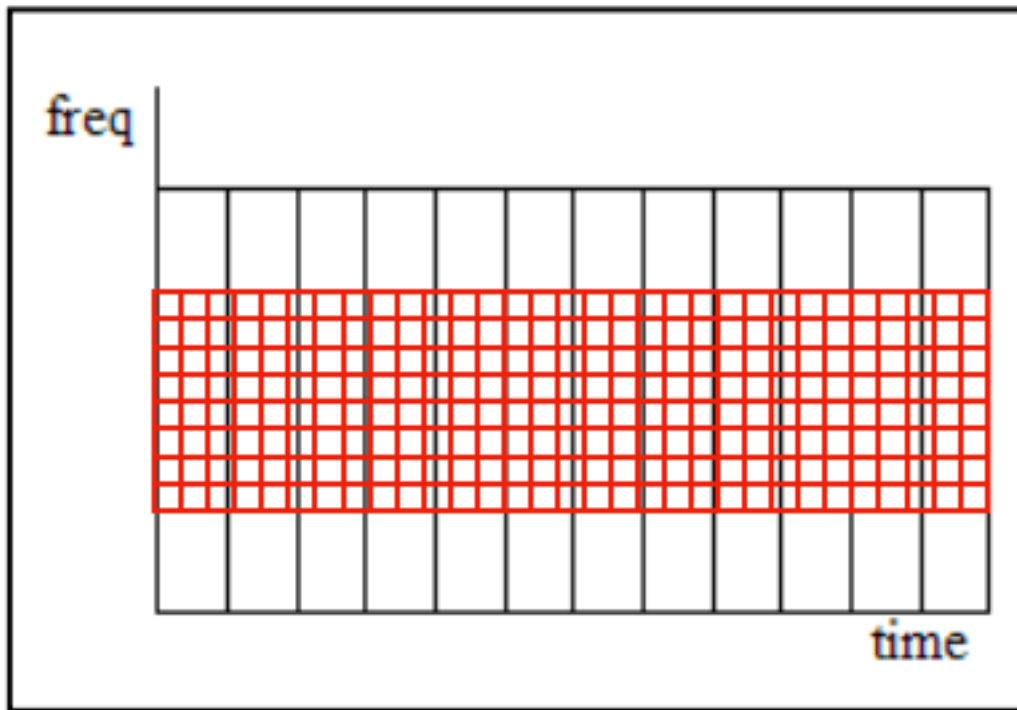


# Better Time and Frequency Resolution

# STFT



# Analytic Signal



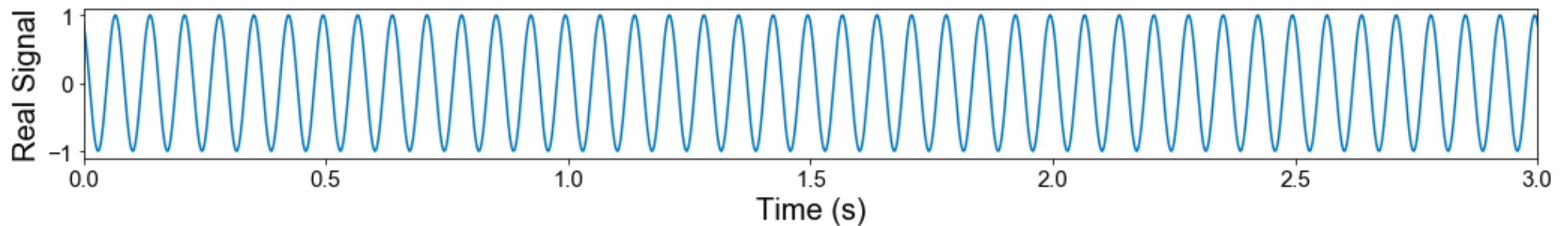
time resolution: **dt**  
frequency resolution: **df**

For a “**well-behaved**” signal:  
(usually) narrowband & denoised

1. Motivate “analytic signals”
2. Understand & derive negative frequencies & DFT symmetry
3. Conceptualize Hilbert Transform



# DFT: Negative Frequencies



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

If you do FT on the first 1s of data, what are the  $X_k$ 's (which ones are not 0)?

**hint:** orthogonality

$$x(n) = \cos(2\pi 14n/N + \theta)$$

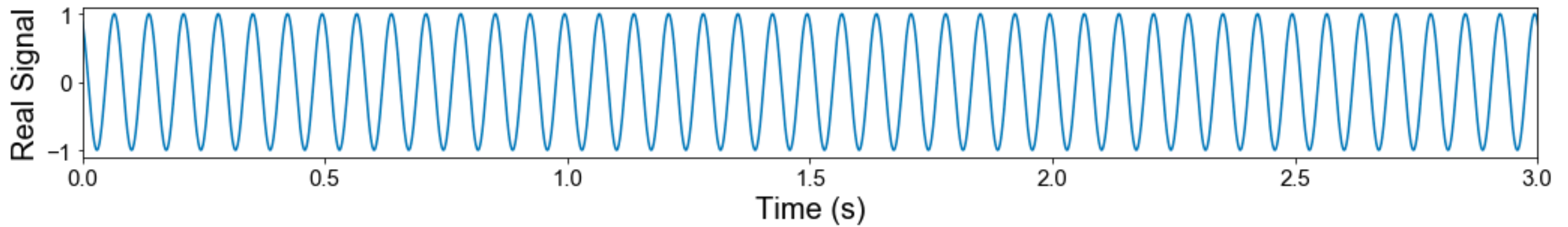
$X_{14} = a - bi$ , rest are 0s...

or are they?

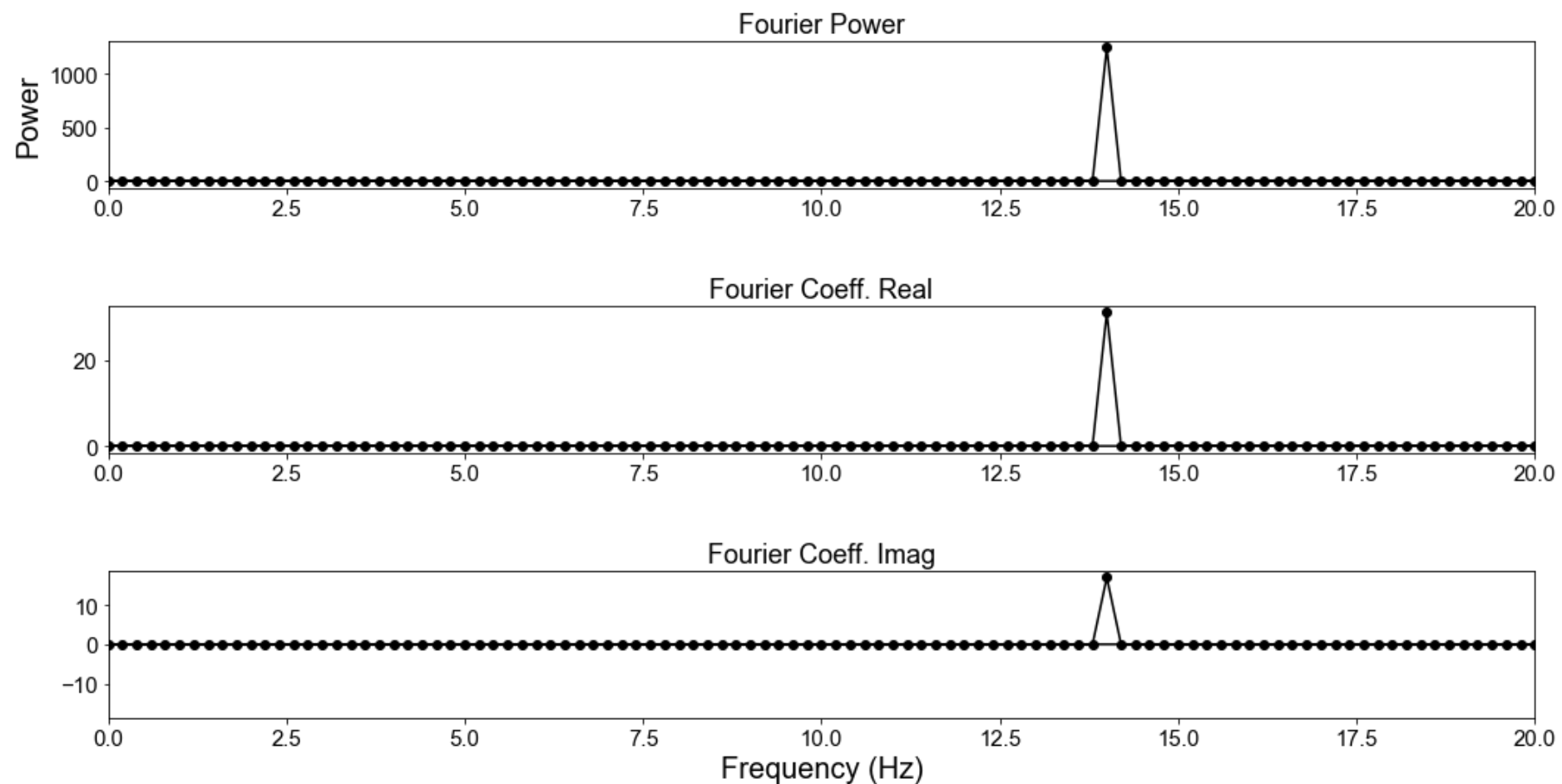




# DFT: Negative Frequencies



What we've been looking at: **positive frequencies**





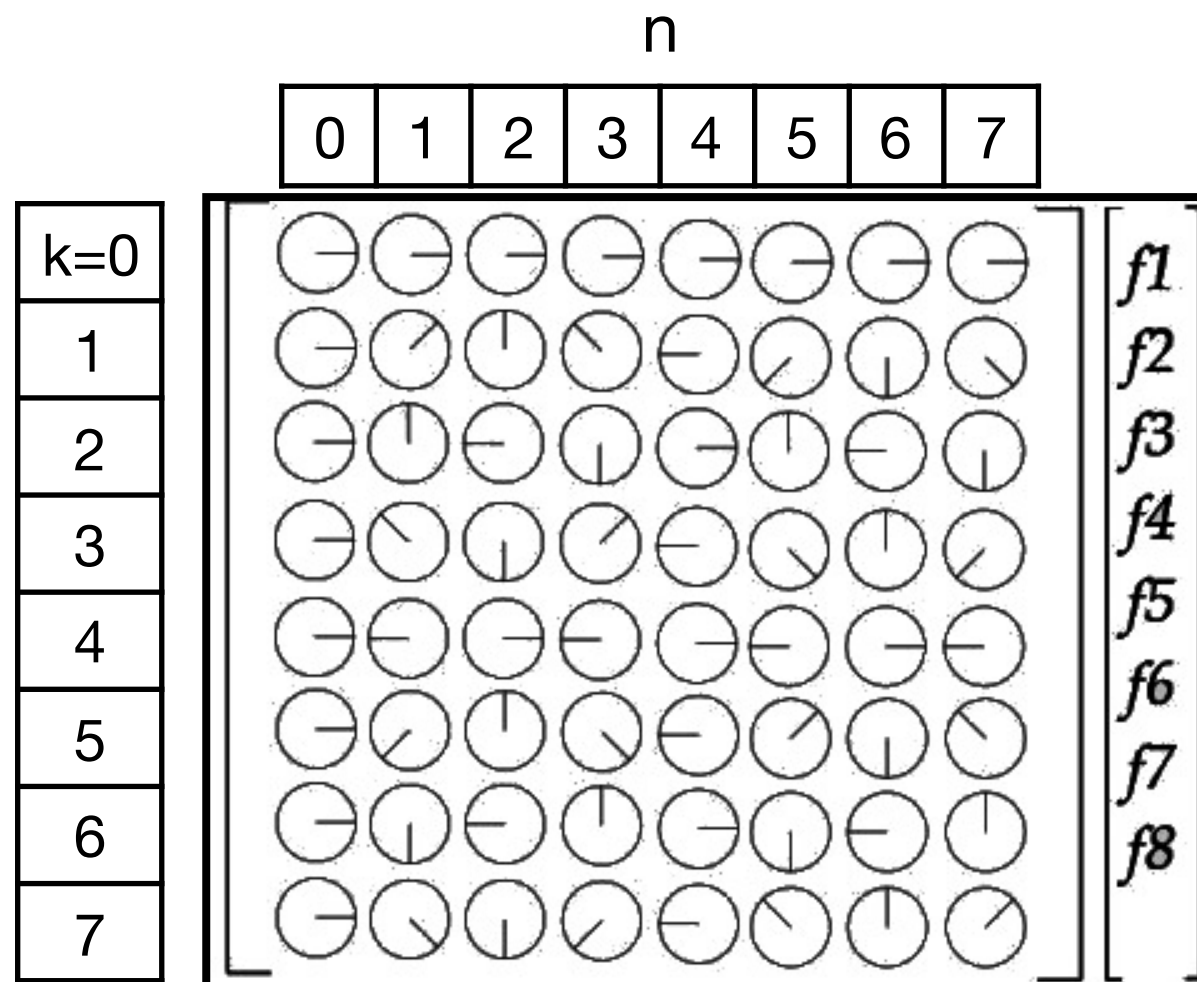
# High School Trig Gymnastics

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

(Eq.1)

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

$k = 0, 1, 2, \dots N-1$



$$\cos(2\pi - \theta) =$$

$$\sin(2\pi - \theta) =$$

$$X_{N-k} = X_{-k}$$

$k = N/2$  is the end  
freq(k) = ?



# High School Trig Gymnastics

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

$$k = 0, 1, 2, \dots, N-1$$

$$\cos(2\pi kn/N) = \cos(-2\pi kn/N) = \cos(2\pi kn/N)$$

$$\sin(2\pi kn/N) = \sin(-2\pi kn/N) = -\sin(2\pi kn/N)$$

if  $x(n)$  **real**, and

$$X_k = a - bi$$

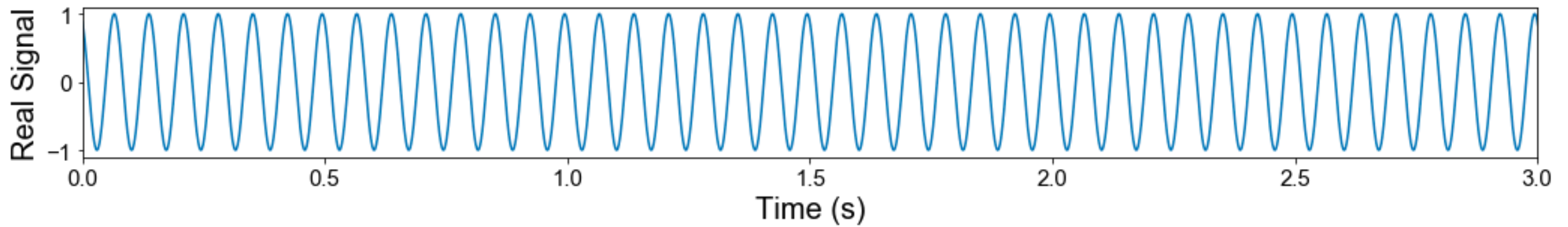
$$X_{N-k} = ?$$

$$a + bi$$

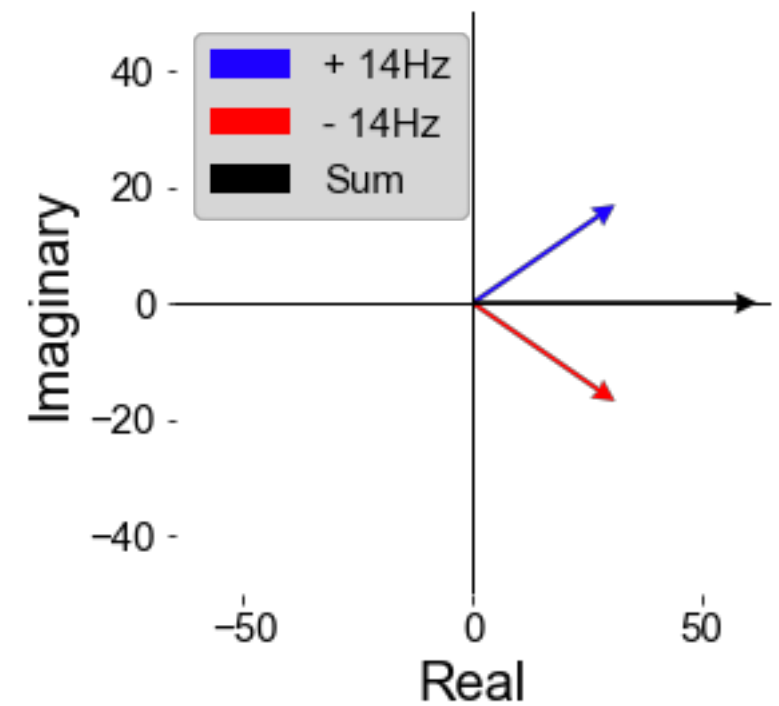
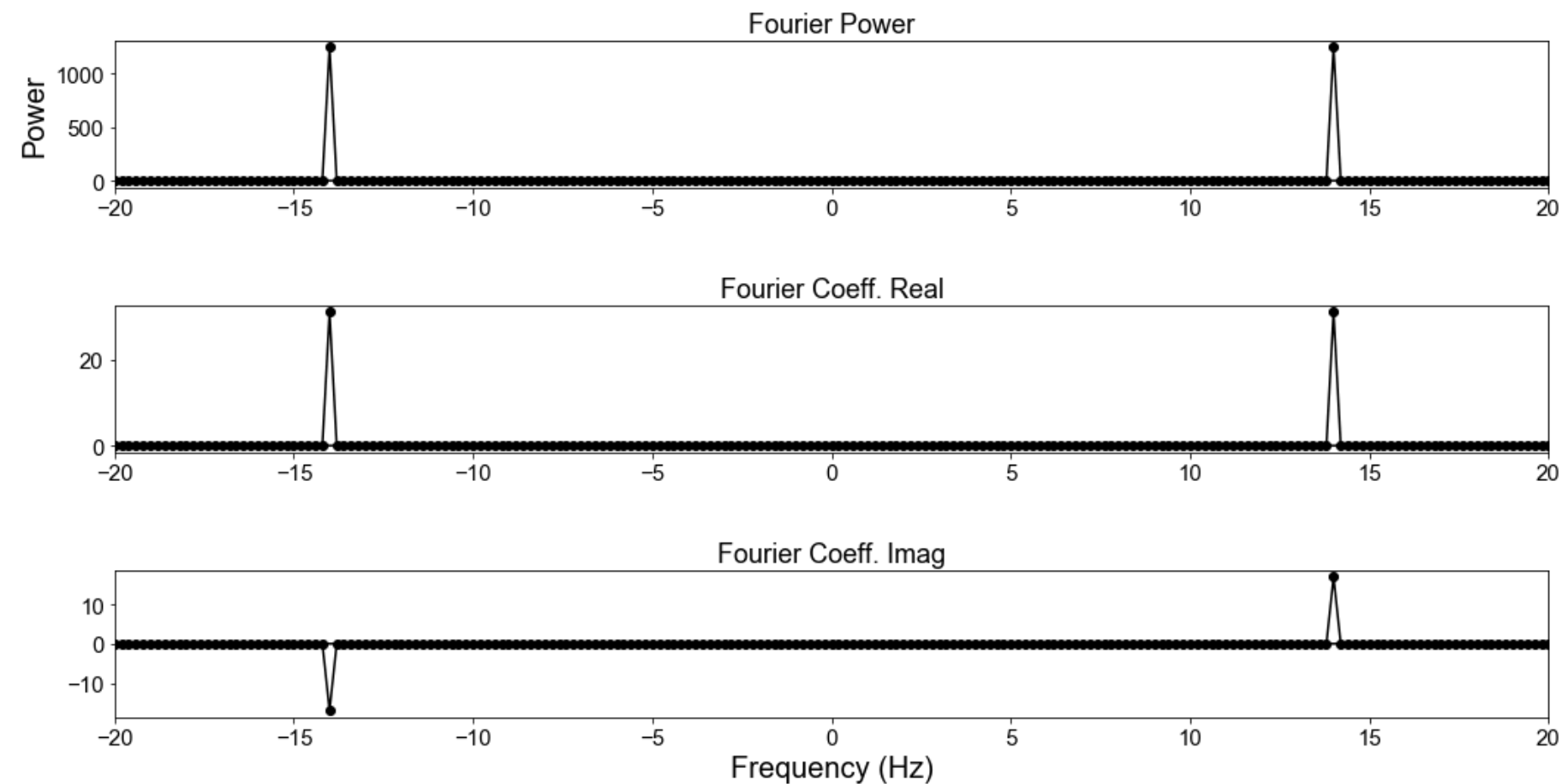
$X_k$  and  $X_{-k}$  are **complex conjugates**.



# DFT: Negative Frequencies



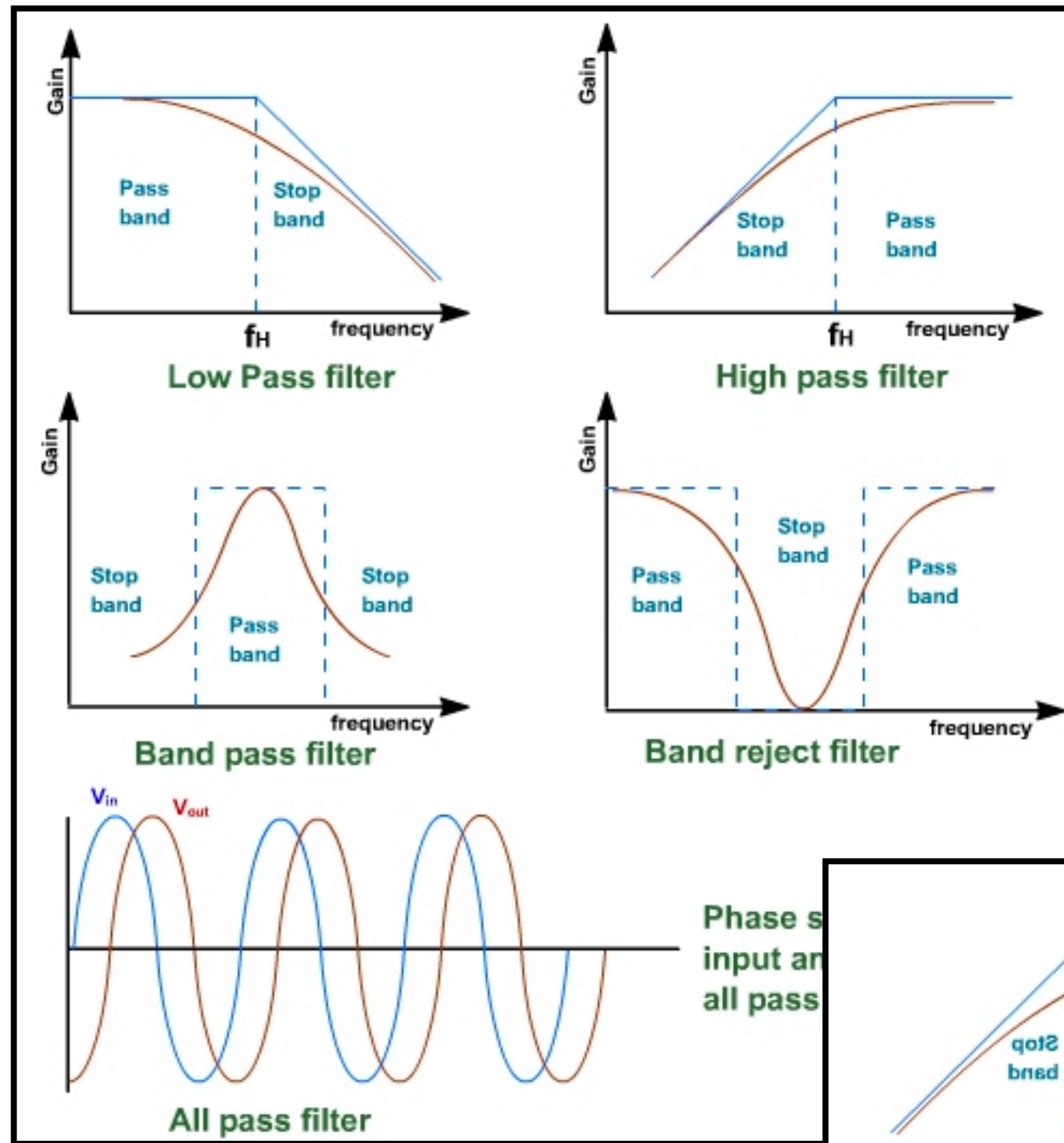
Here's the **full** spectrum: with negative frequencies



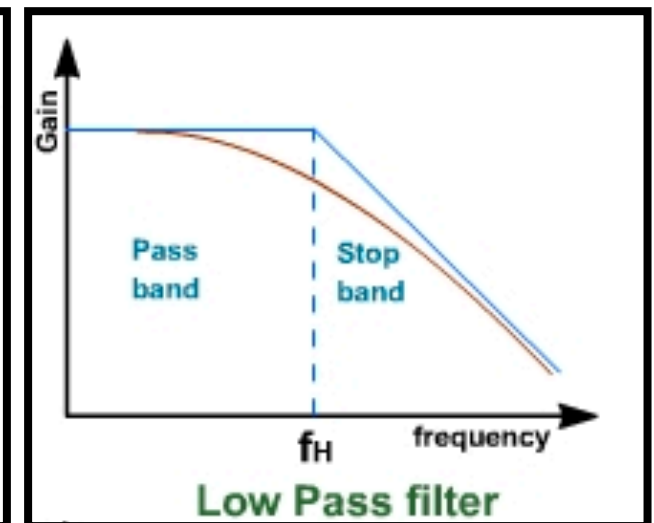
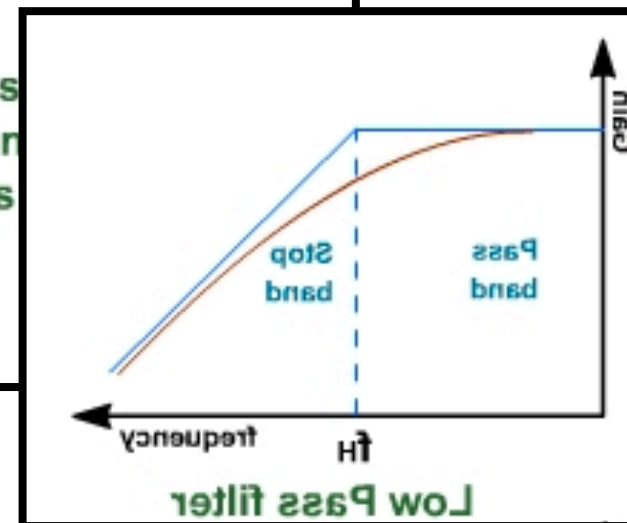
$$x(t) = 2 \cos(\omega_0 t) = e^{j\omega_0 t} + e^{-j\omega_0 t}$$



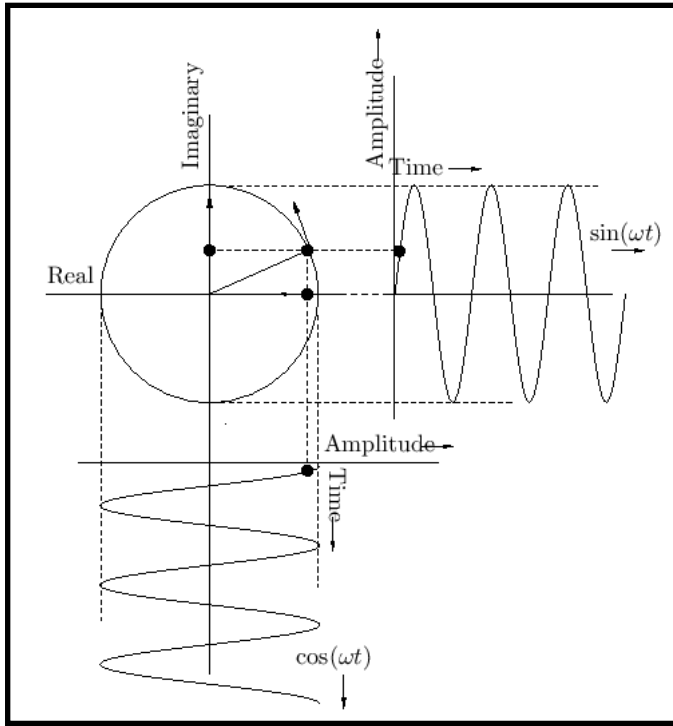
# Filter Response is Symmetric Too



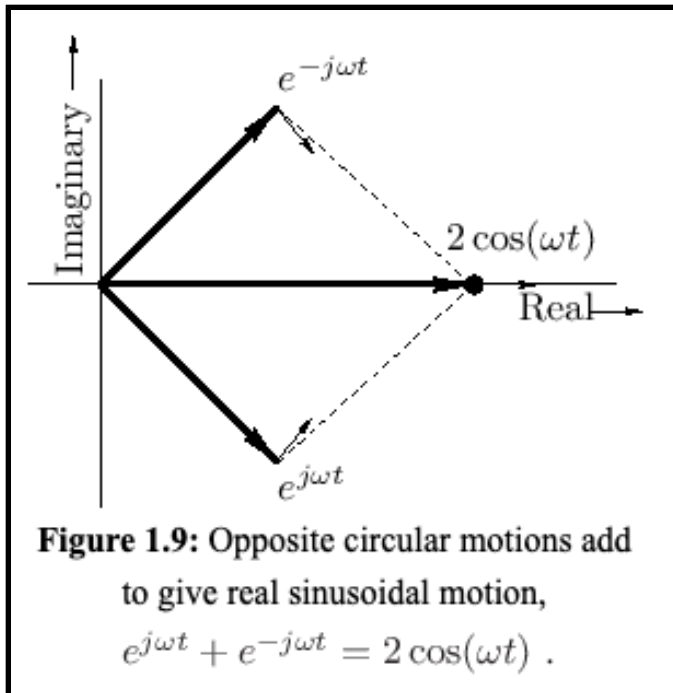
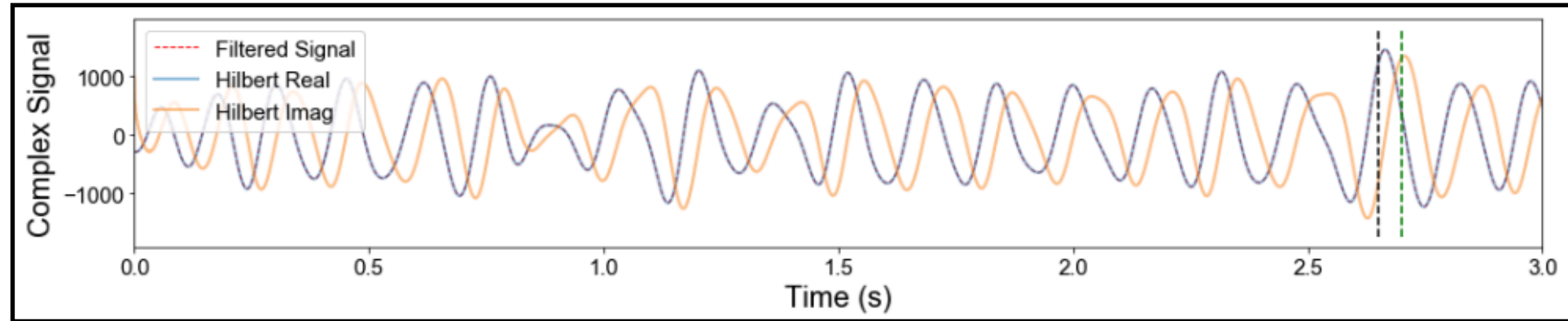
Phase shift  
input and  
all pass



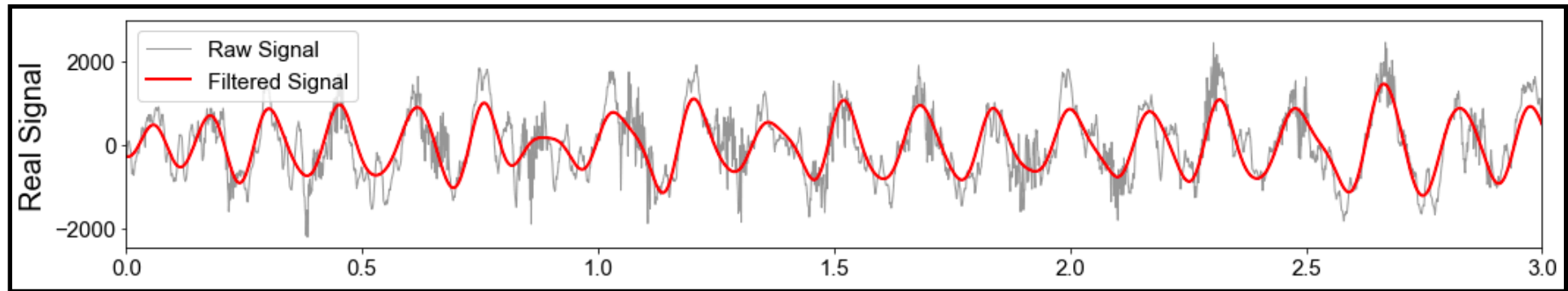
# Cancellation of Imaginary Component



## Analytic (Complex) Signal: a single complex exponential



## Real Signal: sum of 2 complex exponential conjugates



## How to retrieve the analytic signal from the real signal?

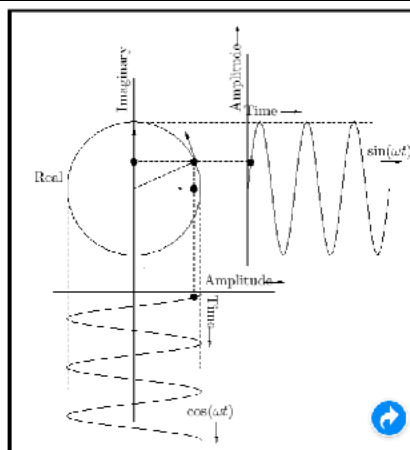


1. Motivate “analytic signals”
2. Understand & derive negative frequencies & DFT symmetry
3. Conceptualize Hilbert Transform





# Hilbert Transform



**Analytic (Complex) Signal:** a single complex exponential

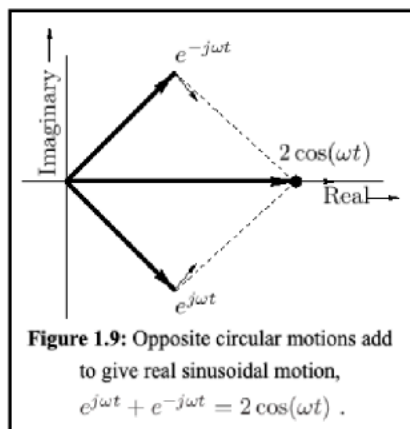
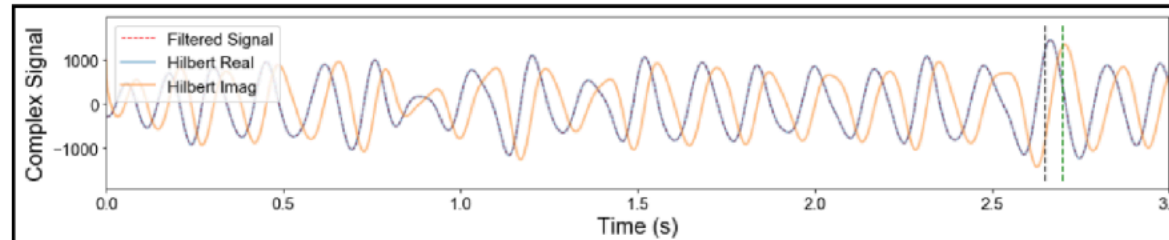
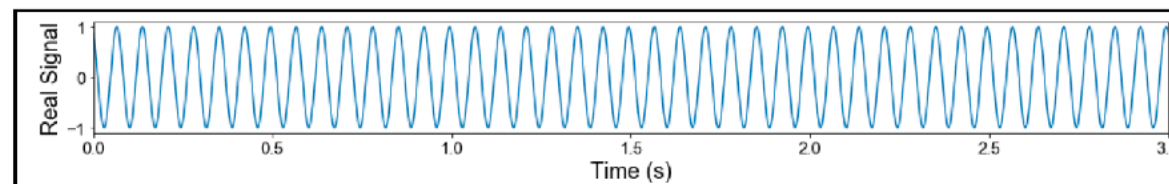


Figure 1.9: Opposite circular motions add to give real sinusoidal motion,  $e^{j\omega t} + e^{-j\omega t} = 2 \cos(\omega t)$ .

**Real Signal:** sum of 2 complex exponential conjugates



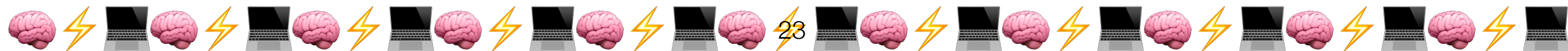
How to retrieve the analytic signal from the real signal?

## scipy.signal.hilbert

`scipy.signal.hilbert(x, N=None, axis=-1)`

Compute the analytic signal, using the Hilbert transform.

The transformation is done along the last axis by default.



## scipy.signal.hilbert

`scipy.signal.hilbert(x, N=None, axis=-1)`

Compute the analytic signal, using the Hilbert transform.

The transformation is done along the last axis by default.

Parameters: `x : array_like`

Signal data. Must be real.

`N : int, optional`

Number of Fourier components. Default: `x.shape[axis]`

`axis : int, optional`

Axis along which to do the transformation. Default: -1.

Returns:

`xa : ndarray`

Analytic signal of `x`, of each 1-D array along `axis`

See also:

[scipy.fftpack.hilbert](#) Return Hilbert transform of a periodic sequence `x`.

### Notes

The analytic signal `x_a(t)` of signal `x(t)` is:

$$x_a = F^{-1}(F(x)2U) = x + iy$$

where  $F$  is the Fourier transform,  $U$  the unit step function, and  $y$  the Hilbert transform of  $x$ . [1]





# Hilbert Transform

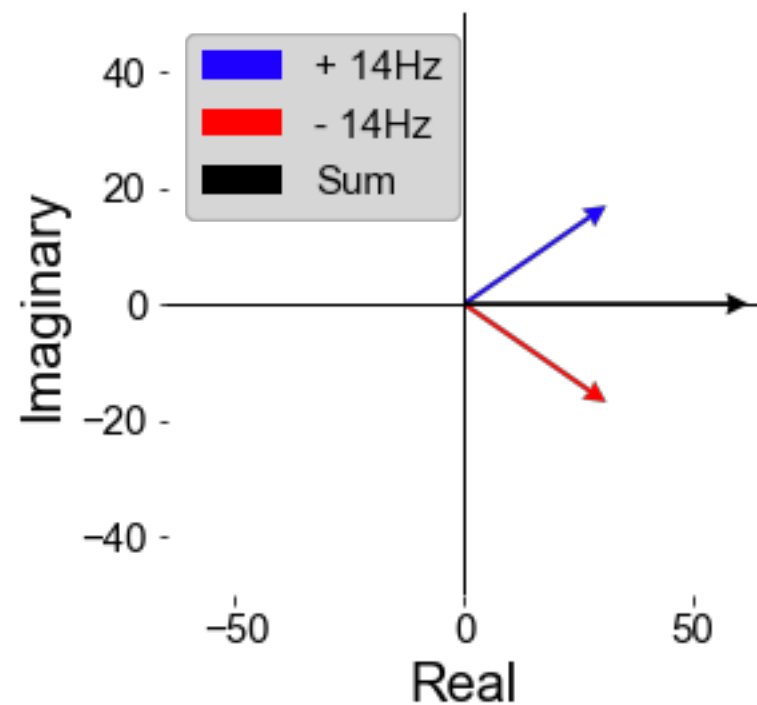
The analytic signal  $x_a(t)$  of signal  $x(t)$  is:

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$U$  is the unit step function:  $U(x) = 1$  for  $x > 0$ , 0 for  $x < 0$

**analytic signal:** FT  $\rightarrow$  lose the negative spectrum  $\rightarrow$  inverse FT



$y$  is the “Hilbert Transform” of  $x$ .

“Hilbert Transform” is also the operation.

You might also hear “Hilbert Transform” to mean the analytic signal.



# Hilbert Transform

The analytic signal  $x_a(t)$  of signal  $x(t)$  is:

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**analytic signal:** FT  $\rightarrow$  lose the negative spectrum  $\rightarrow$  inverse FT

Time Domain Convolution

$$H(u)(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{u(\tau)}{t - \tau} d\tau,$$
$$1/(\pi t)$$

Frequency Domain Multiply

$$\mathcal{F}(H(u))(\omega) = (-i \operatorname{sgn}(\omega)) \cdot \mathcal{F}(u)(\omega)$$

$$\sigma_H(\omega) = \begin{cases} i = e^{+\frac{i\pi}{2}}, & \text{for } \omega < 0 \\ 0, & \text{for } \omega = 0 \\ -i = e^{-\frac{i\pi}{2}}, & \text{for } \omega > 0 \end{cases}$$



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## Analytic Signals and Hilbert Transform Filters

A signal which has no **negative-frequency** components is called an *analytic signal*.<sup>4.12</sup> Therefore, in continuous time, every analytic signal  $z(t)$  can be represented as

$$z(t) = \frac{1}{2\pi} \int_0^\infty Z(\omega) e^{j\omega t} d\omega$$

where  $Z(\omega)$  is the complex coefficient (setting the amplitude and phase) of the positive-frequency complex **sinusoid**  $\exp(j\omega t)$  at frequency  $\omega$ .

Any real **sinusoid**  $A \cos(\omega t + \phi)$  may be converted to a positive-frequency **complex sinusoid**

$A \exp[j(\omega t + \phi)]$  by simply generating a **phase-quadrature** component  $A \sin(\omega t + \phi)$  to serve as the ``imaginary part":

$$Ae^{j(\omega t + \phi)} = A \cos(\omega t + \phi) + jA \sin(\omega t + \phi)$$



1. Motivate “analytic signals”
2. Understand & derive negative frequencies & DFT symmetry
3. Conceptualize Hilbert Transform

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



## Bloom's Taxonomy

