

# Question of the Day

Is eating 10 strawberries and a banana the same as drinking a strawberry banana smoothie?

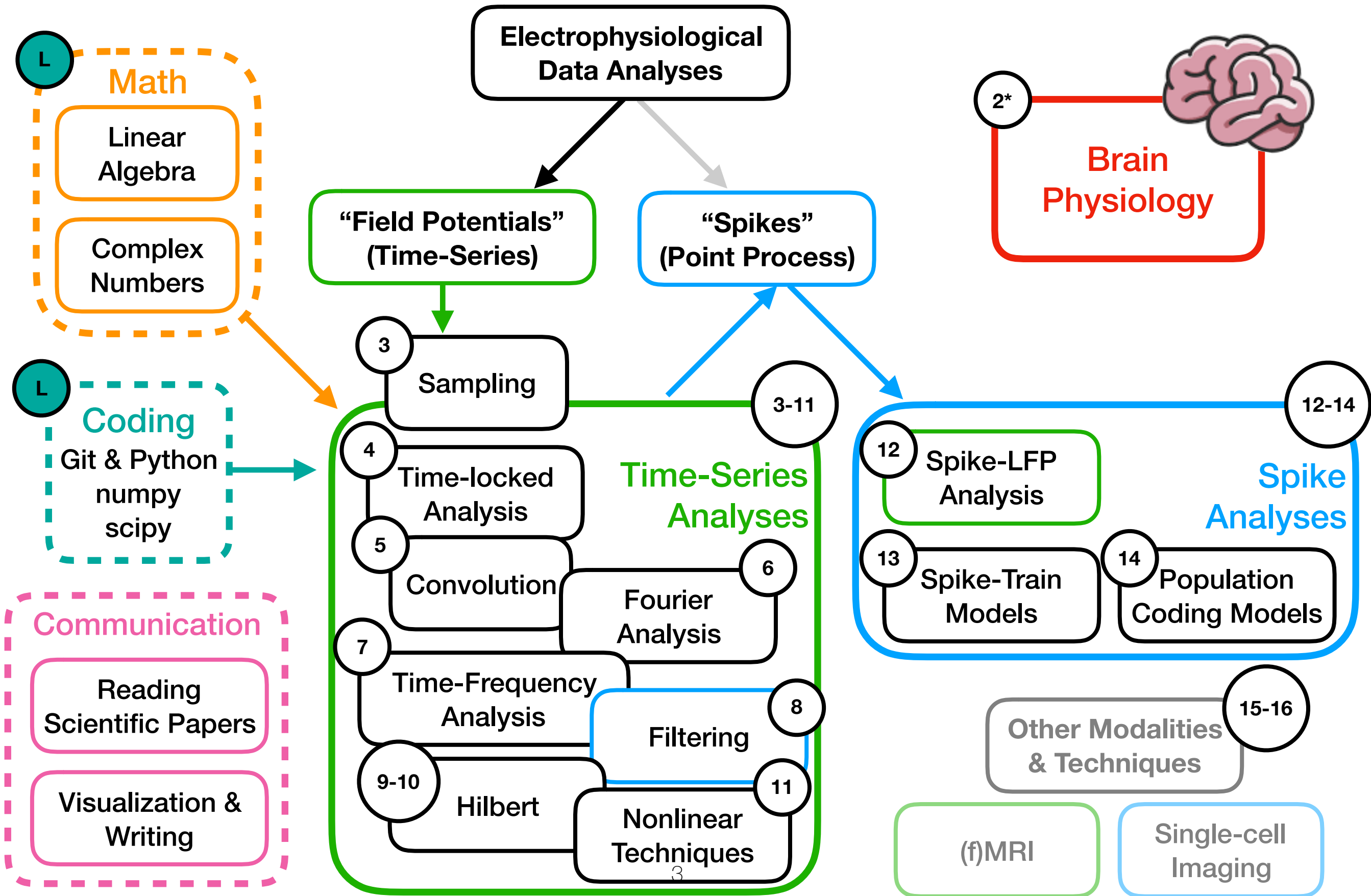


# LTI Systems and Convolution

**Lecture 5**  
**July 9, 2019**



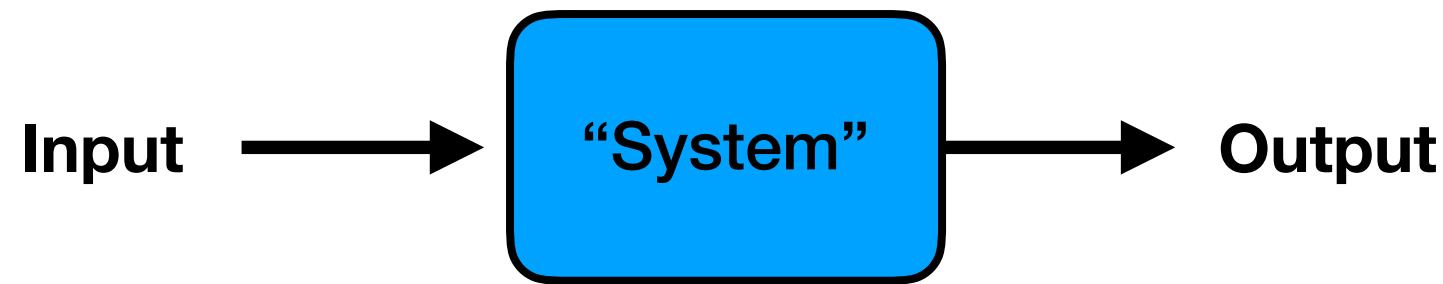
# Course Outline: Road Map



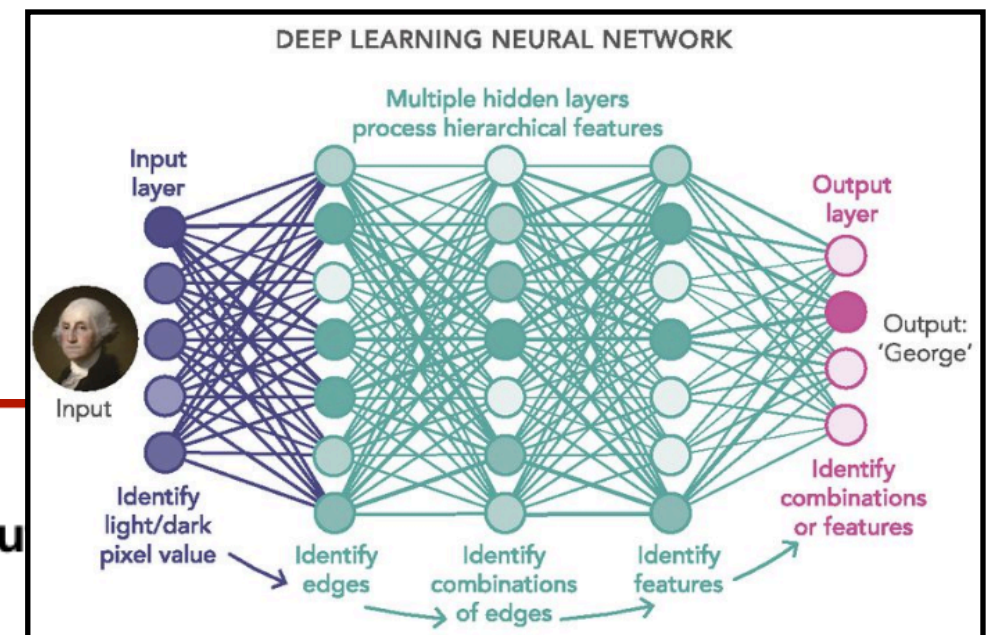
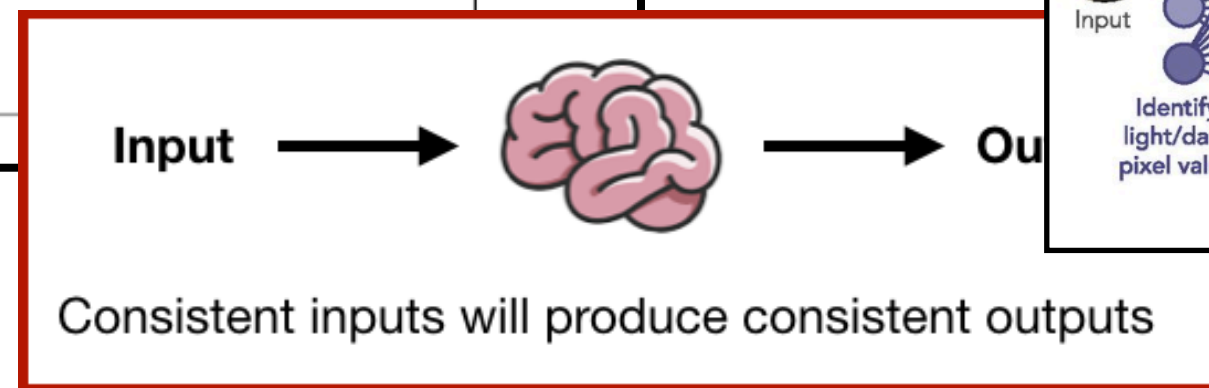
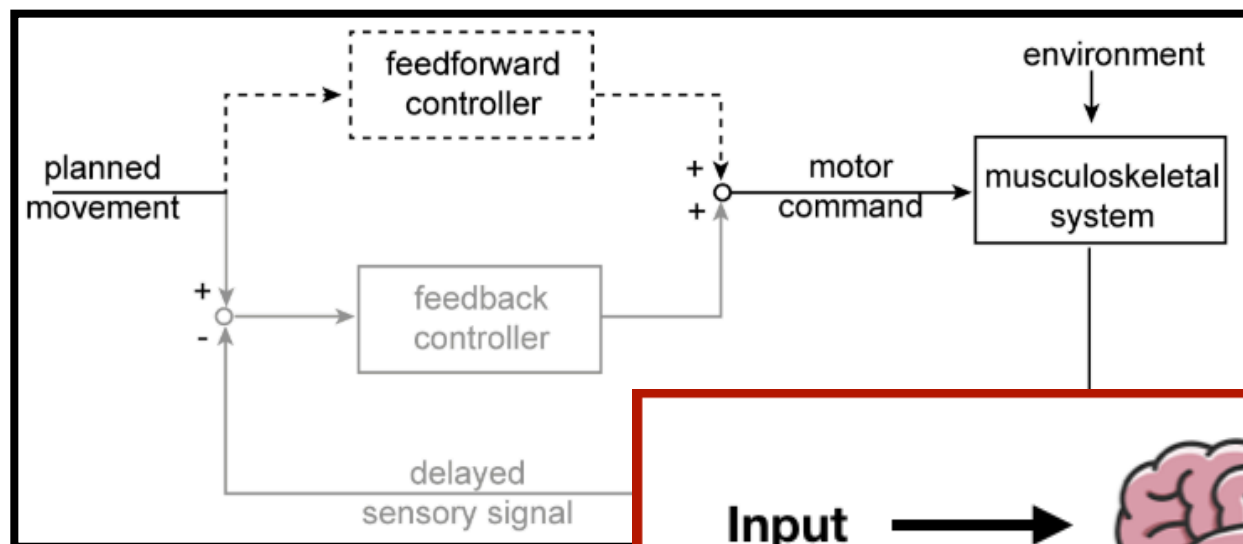
1. Formally define LTI systems
2. Convolution & impulse response
3. Introduce the frequency domain



# Systems Perspective



The “system” performs a set of transformations on the input, to produce the output.



List 5 examples of systems: their input, output, and transformation.  
Be imaginative!



# Systems Perspective

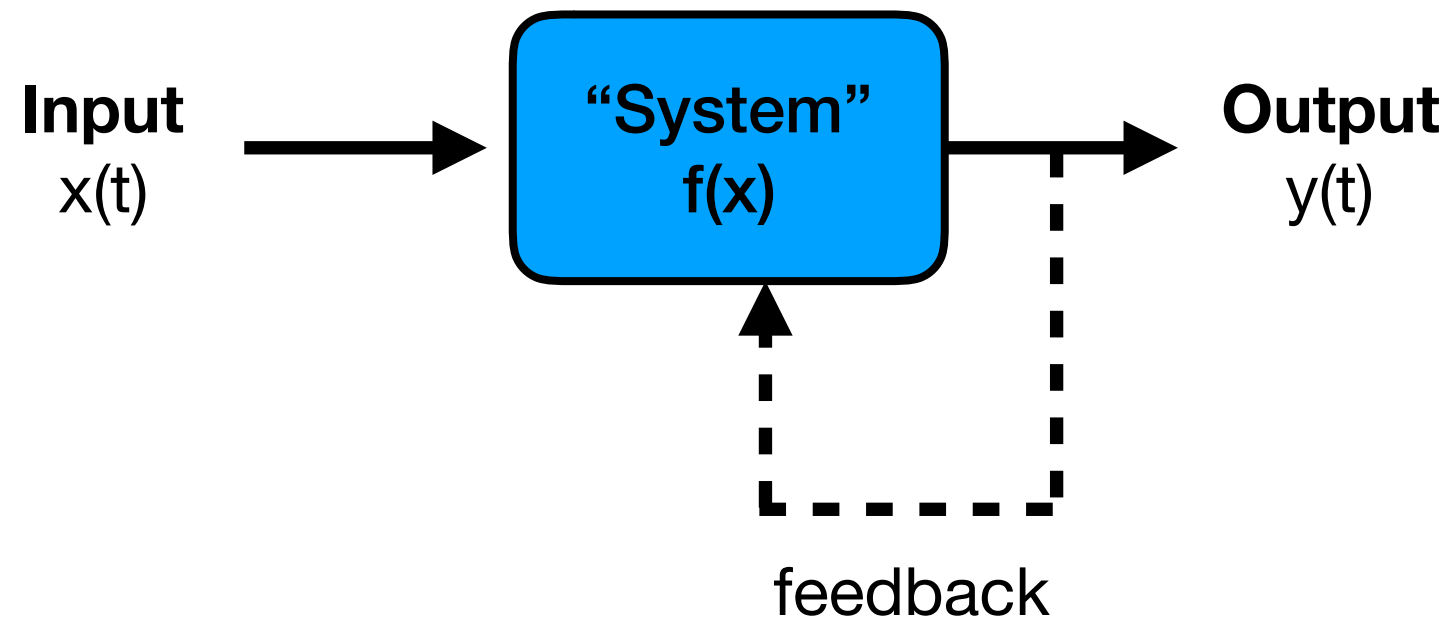
System	Input	Transformation	Output	Linear?	Time Invariant?
school	students teachers resources/ funding	education/classes	degrees/skills		
computer	money people	communication/ money processing	Coachella tickets		
lactose intolerant digestive system	milk	digest everything else	lack of output		



# Linear Time Invariant (LTI) Systems

Real-life systems are very complex (non-linear).

**Engineering approach:** assume “**linearity**” and/or find linear range,  
and usually “**time invariance**”

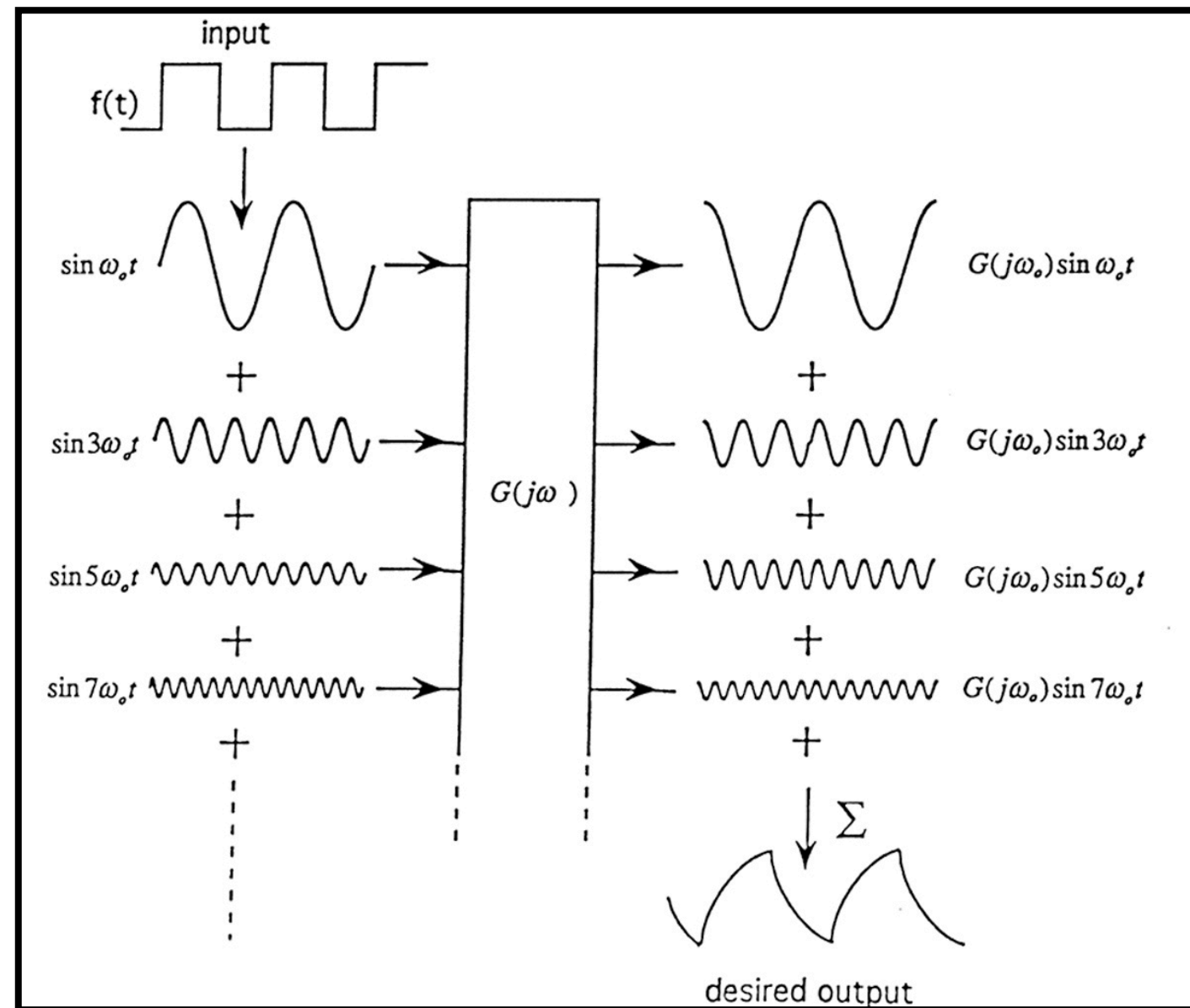


$$y(t) = f(x_1(t) + x_2(t)) = f(x_1(t)) + f(x_2(t))$$

$$y(t) = f(Cx_1(t)) = Cf(x_1(t)), C = \text{constant}$$

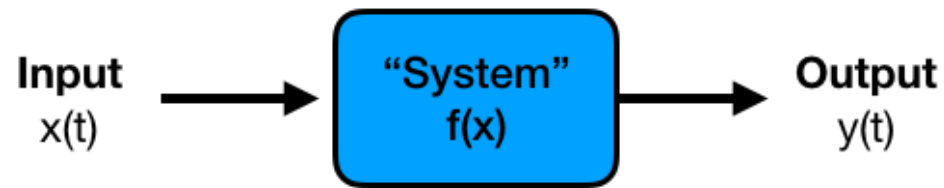
**In English:** adding together the result of the operation on the components separately **is equivalent** to acting on the sum of the components.

**The whole is NOT greater than the sum of the parts.**





# Linear or Not?



$$y(t) = f(x_1(t) + x_2(t)) = f(x_1(t)) + f(x_2(t))$$

$$y(t) = f(Cx_1(t)) = Cf(x_1(t)), C = \text{constant}$$

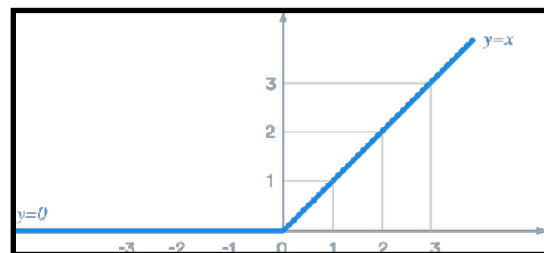
$$f(x) = x$$

$$f(x) = x^2$$

$$f(x) = x + C, C = \text{constant}$$

$$f(x) = \text{dot}(\vec{w}, \vec{x})$$

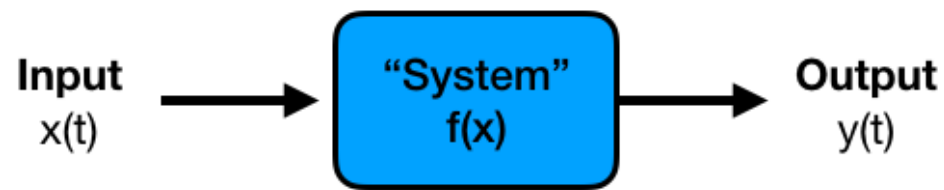
$$f(x) = \text{ReLU}$$



Selling fruits (\$1/apples and \$0.5/oranges)



# Linear or Not?



$$y(t) = f(x_1(t) + x_2(t)) = f(x_1(t)) + f(x_2(t))$$

$$y(t) = f(Cx_1(t)) = Cf(x_1(t)), C = \text{constant}$$

$$f(x) = x$$

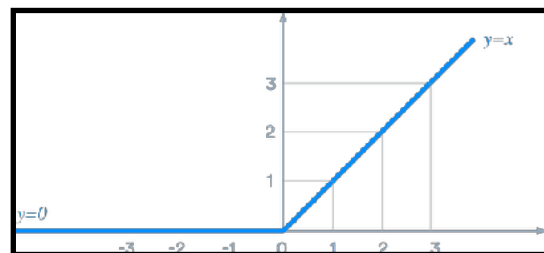
$$f(x) = x^2$$

$$f(x) = x + C, C = \text{constant}$$

In general, some combination of adding **signals** and multiplying by **constants** will produce a linear operation.

$$f(x) = \text{dot}(\vec{w}, \vec{x})$$

$$f(x) = \text{ReLu}$$

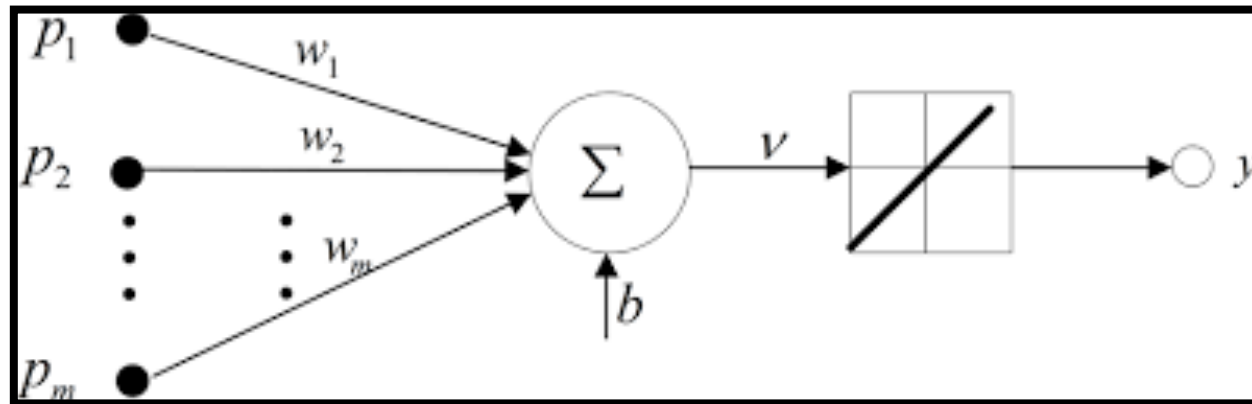


Selling fruits (\$1/apples and \$0.5/oranges)



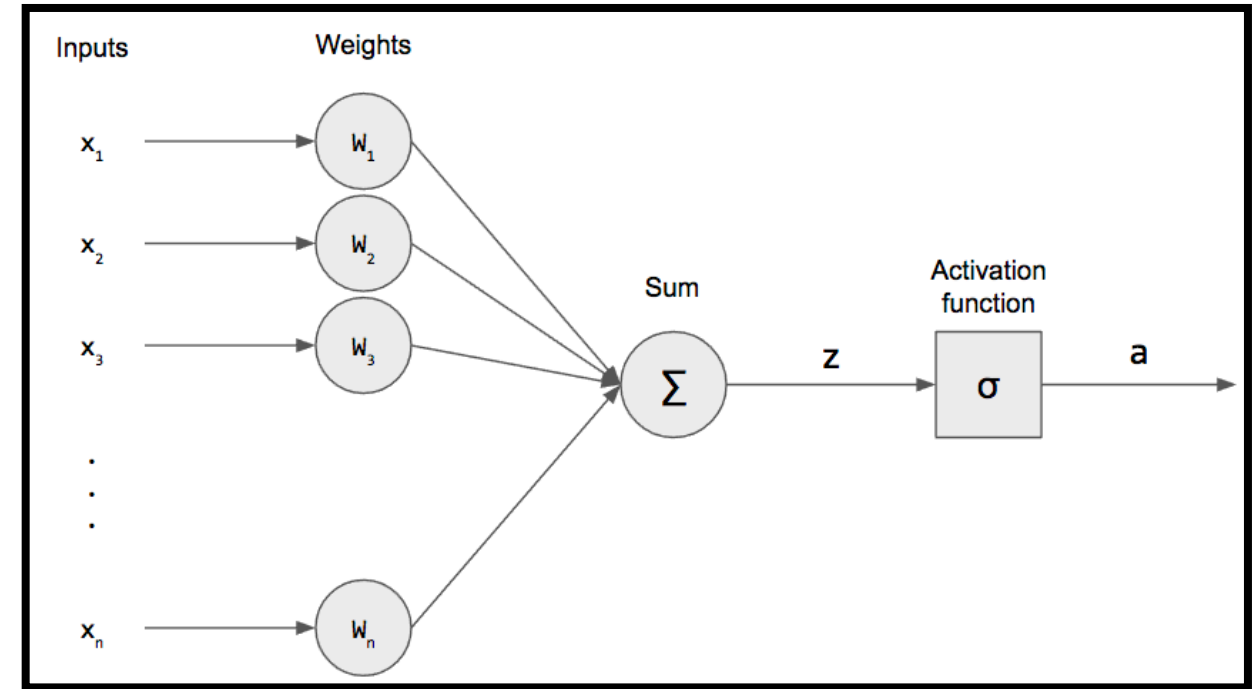
# Neural Networks

## Linear Network

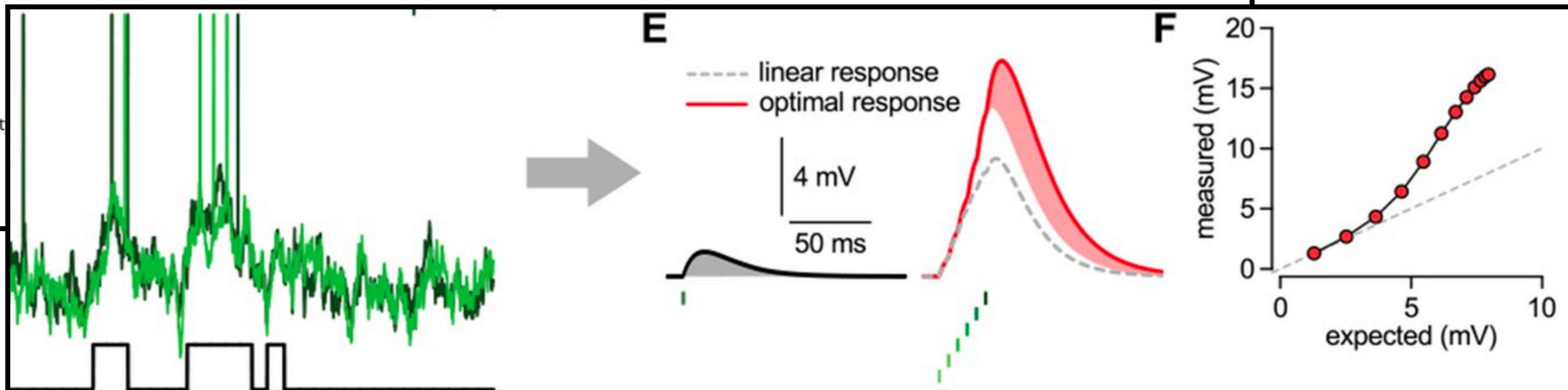


Nonlinearity introduces **a lot** of computational complexity.

## Non-Linear Network



Dendritic nonlinearities are tuned for efficient spike-based computations in cortical circuits



# Time-Invariance

$$y(t) = f(x_1(t)) \rightarrow y(t + \tau) = f(x_1(t + \tau)), \tau = \text{constant}$$

**In English:** operating on the delayed signal will produce a delayed output.

Or, acting on the same signal later will produce the same result later.

**Time-Invariant**

e.g., selling fruits  
(mostly)

**Not Time-Invariant**

e.g., time dilation

$$f(x(t)) = x(2t)$$



# Systems Perspective

System	Input	Transformation	Output	Linear?	Time Invariant?
school	students teachers resources/ funding	education/classes	degrees/skills	no	no
computer	money people	communication/ money processing	Coachella tickets	yes*	no
lactose intolerant digestive system	milk	digest everything else	lack of output	yes*	yes*

Real-world & natural systems are almost never completely LTI.  
Always define the range over which they are.



1. Formally define LTI systems
2. Convolution & impulse response
3. Introduce the frequency domain

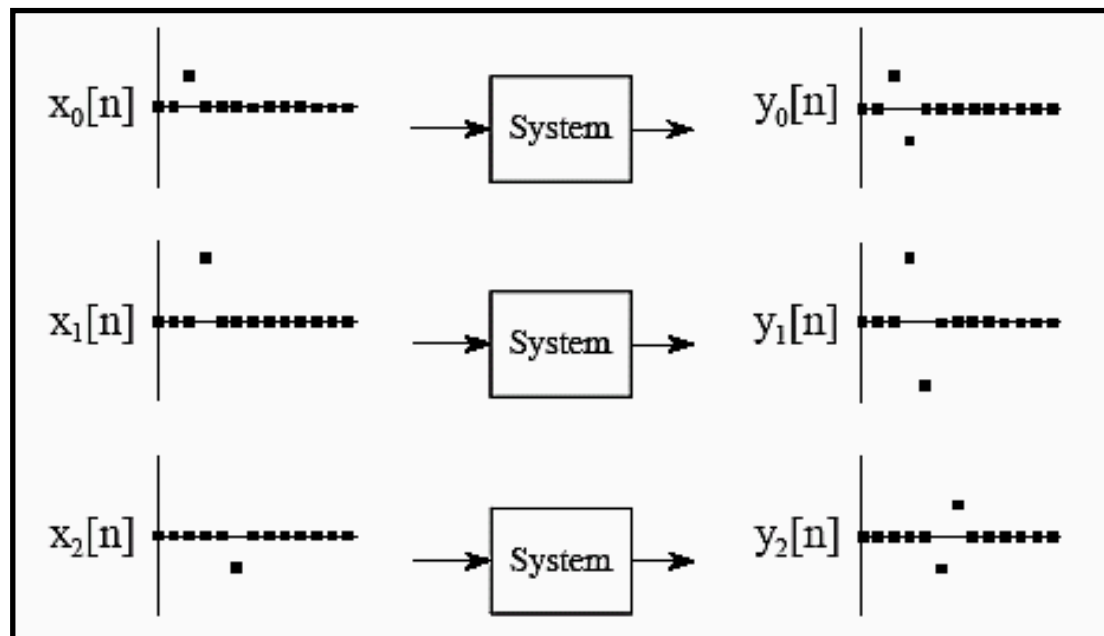


# Why LTI?

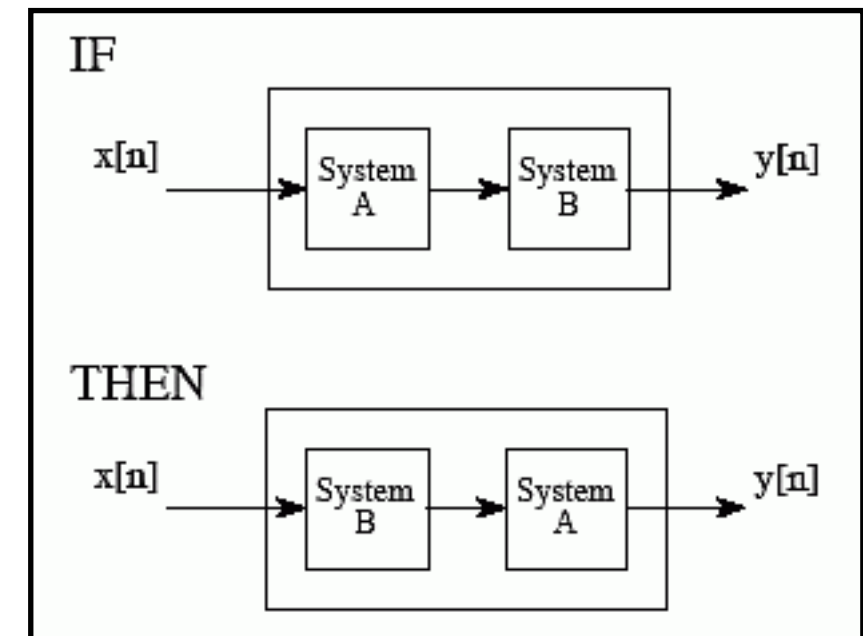
System are almost never LTI, so why bother **modeling** and **analyzing** them as such?

**Answer:** because it allows us to break up (decompose) complex transformations and signals, both **in components** and **in time**.

Additive



Commutative



# Foundation of Digital Signal Processing

**Intuition:** we know exactly how your body responds when you eat various fruits, but we have no idea what drinking a smoothie would do. How can we infer your body's response?

**Digital Signal Processing (DSP):**  
divide (decomposition) and conquer (transformation)

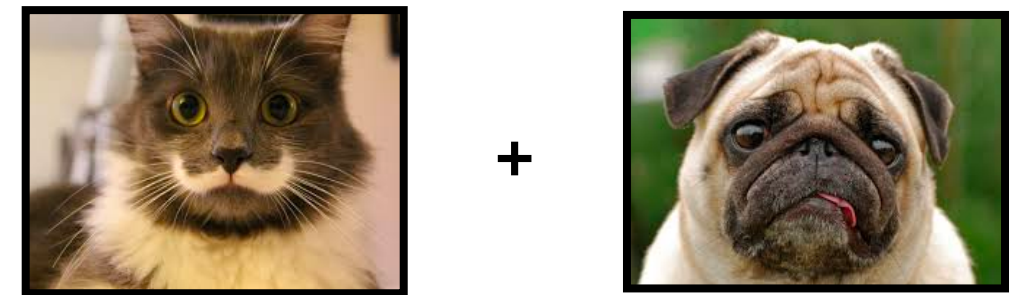
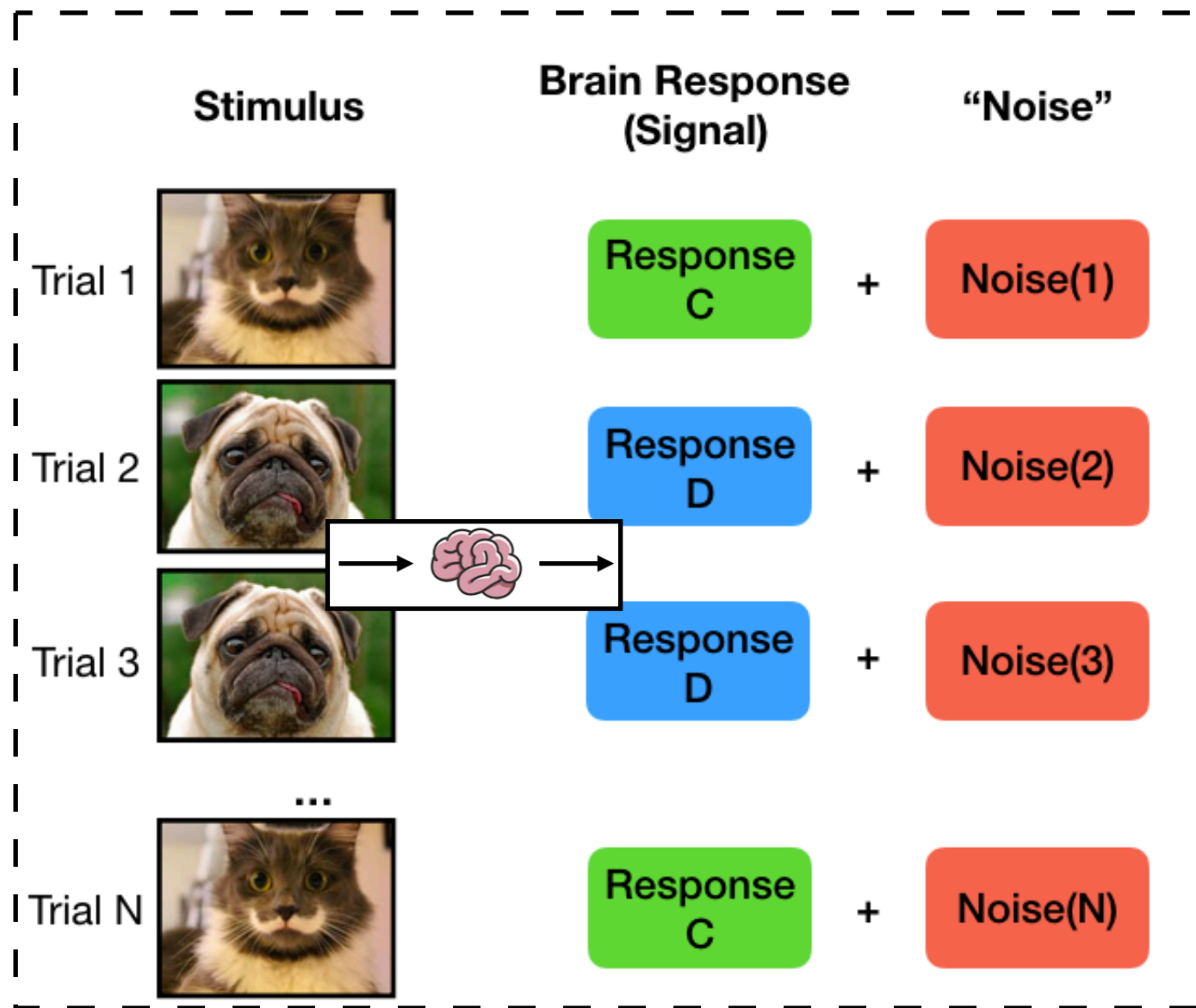
**Impulse Response**

**Frequency Decomposition**





# Impulse Response



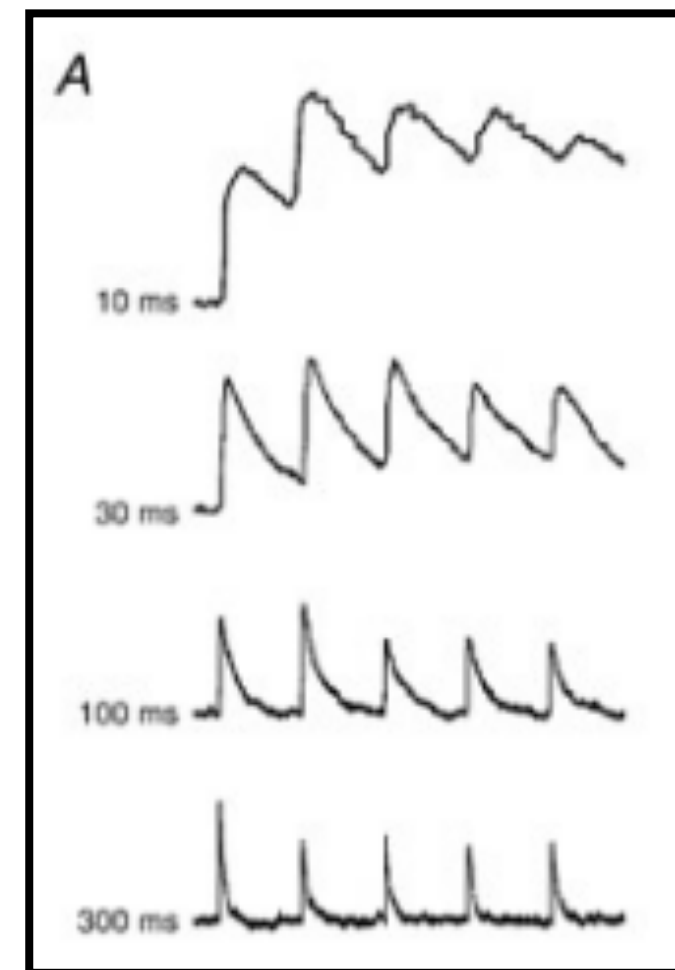
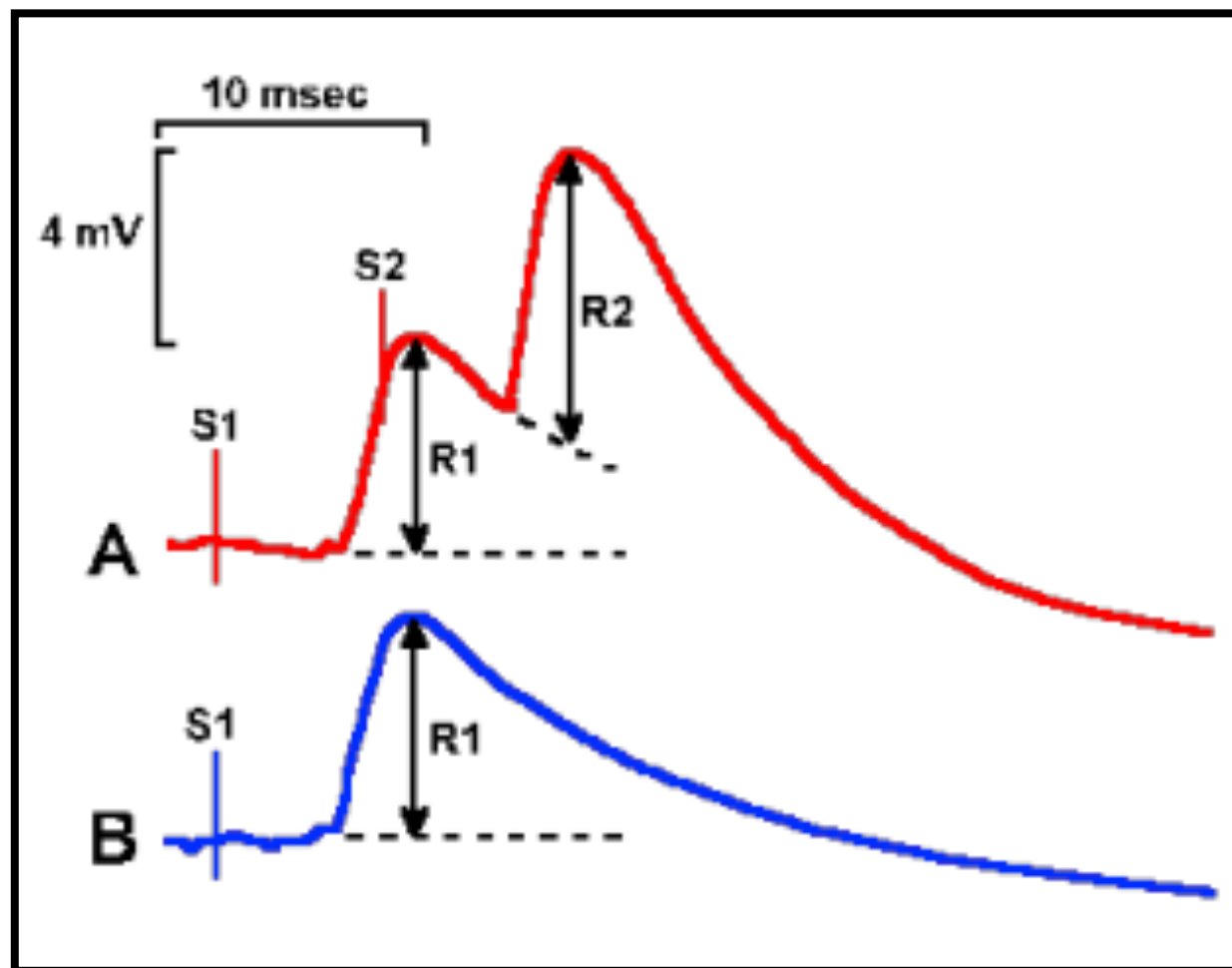
What will the combined brain response be?



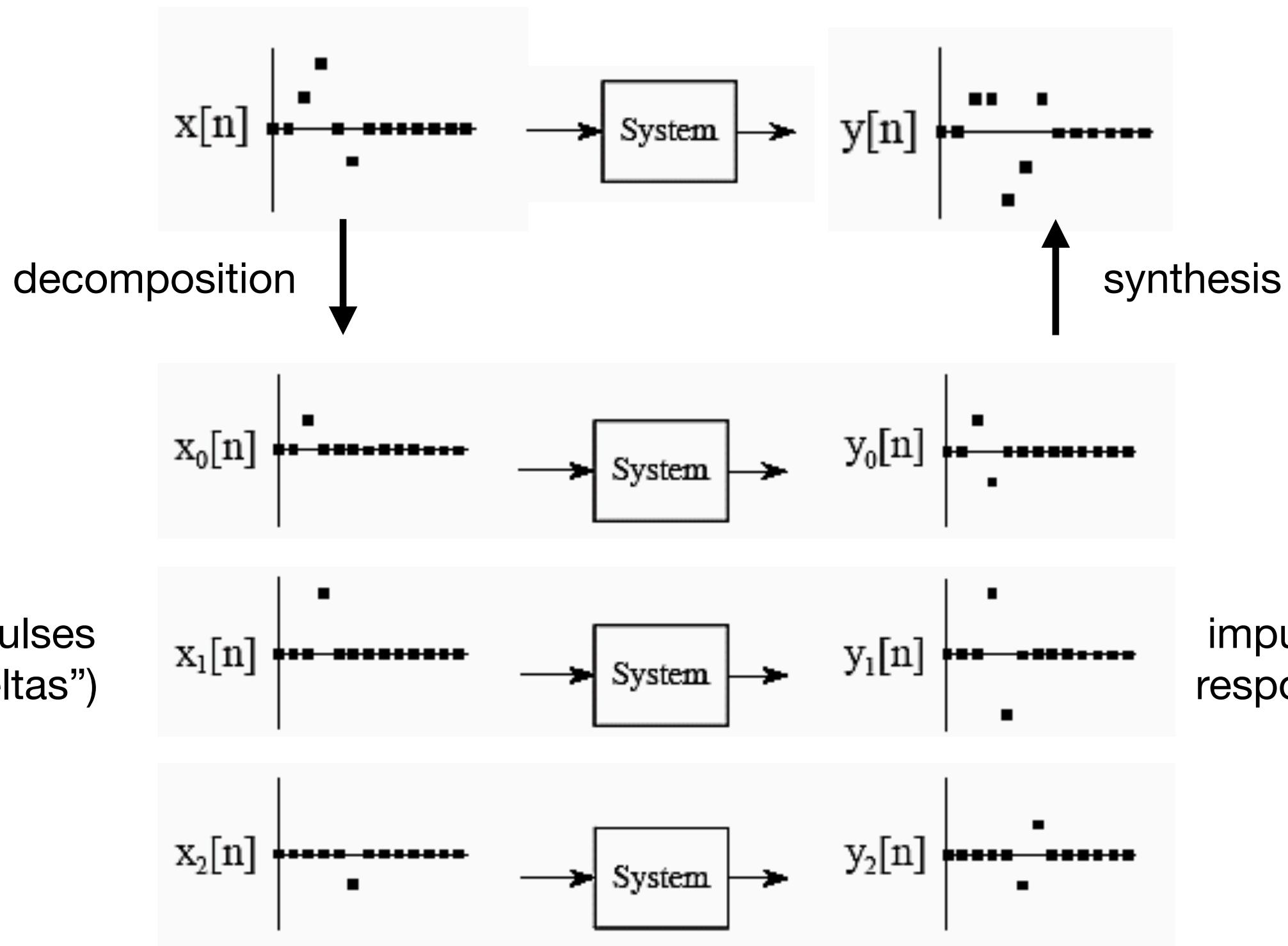
# Synaptic Response as Impulse Response

The same synaptic potential is triggered by an action potential, no matter when, and are summed over time.

\*\* This is an ideal approximation



# Impulse Response



# Delta Function & Impulse

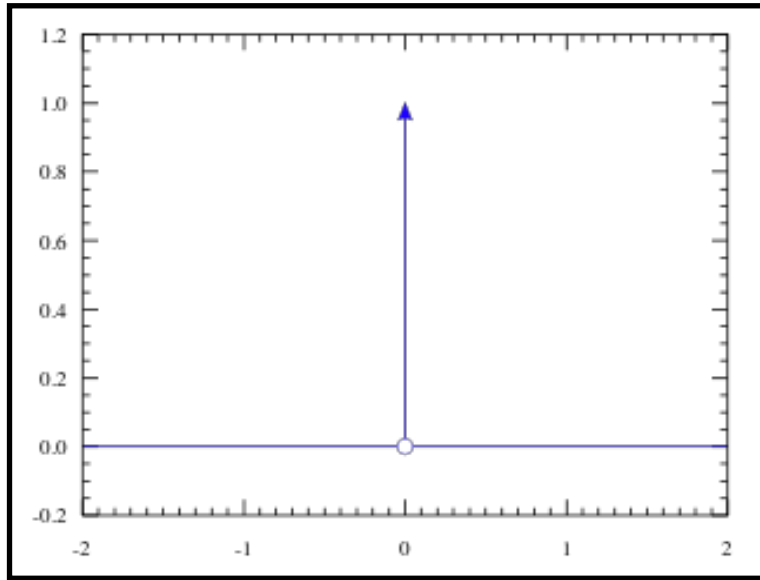
## Continuous Time: Dirac's Delta (Approximation at the Limit)

$$\delta(t)$$

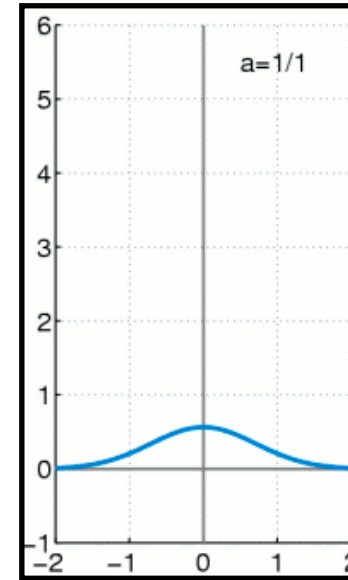
$$\delta(x) = \begin{cases} +\infty, & x = 0 \\ 0, & x \neq 0 \end{cases}$$

$$\int_{-\infty}^{\infty} \delta(x) dx = 1.$$

*(x is t here)*



time

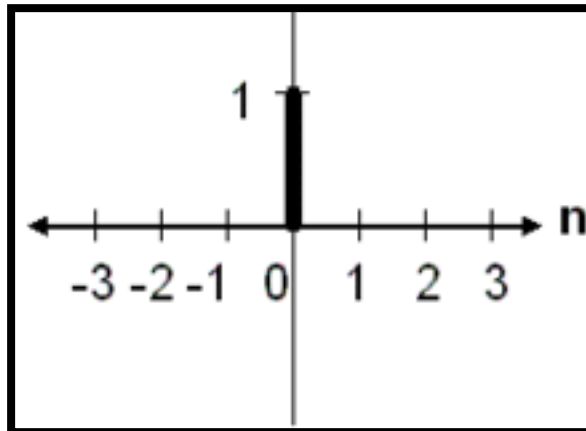


## Very hairy!

## Discrete Time (Kronecker Delta)

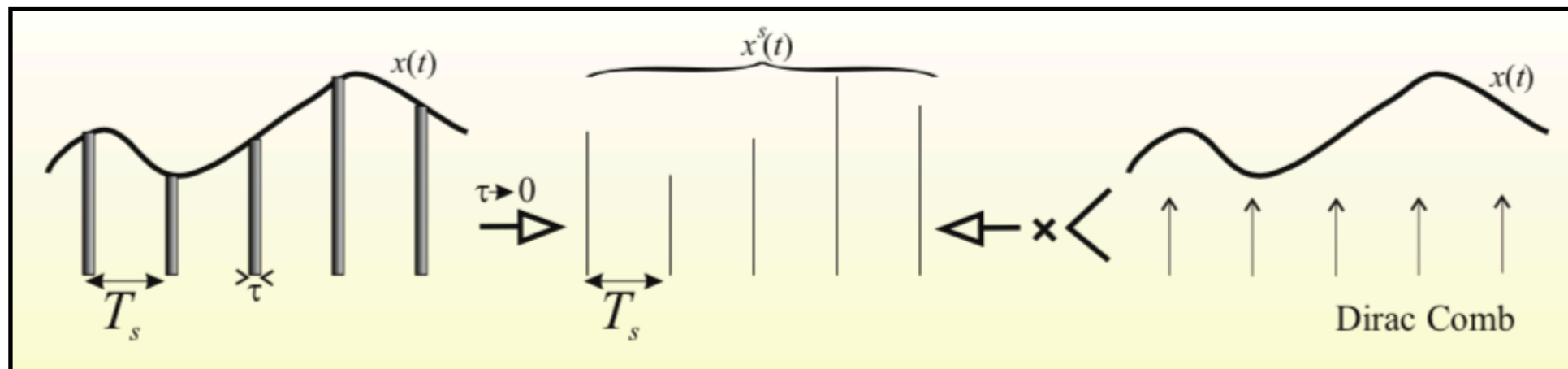
$$\delta(n)$$

$$\delta[n] = \begin{cases} 0, & n \neq 0 \\ 1, & n = 0. \end{cases}$$



# Nice!

# Delta Function & Digital Sampling

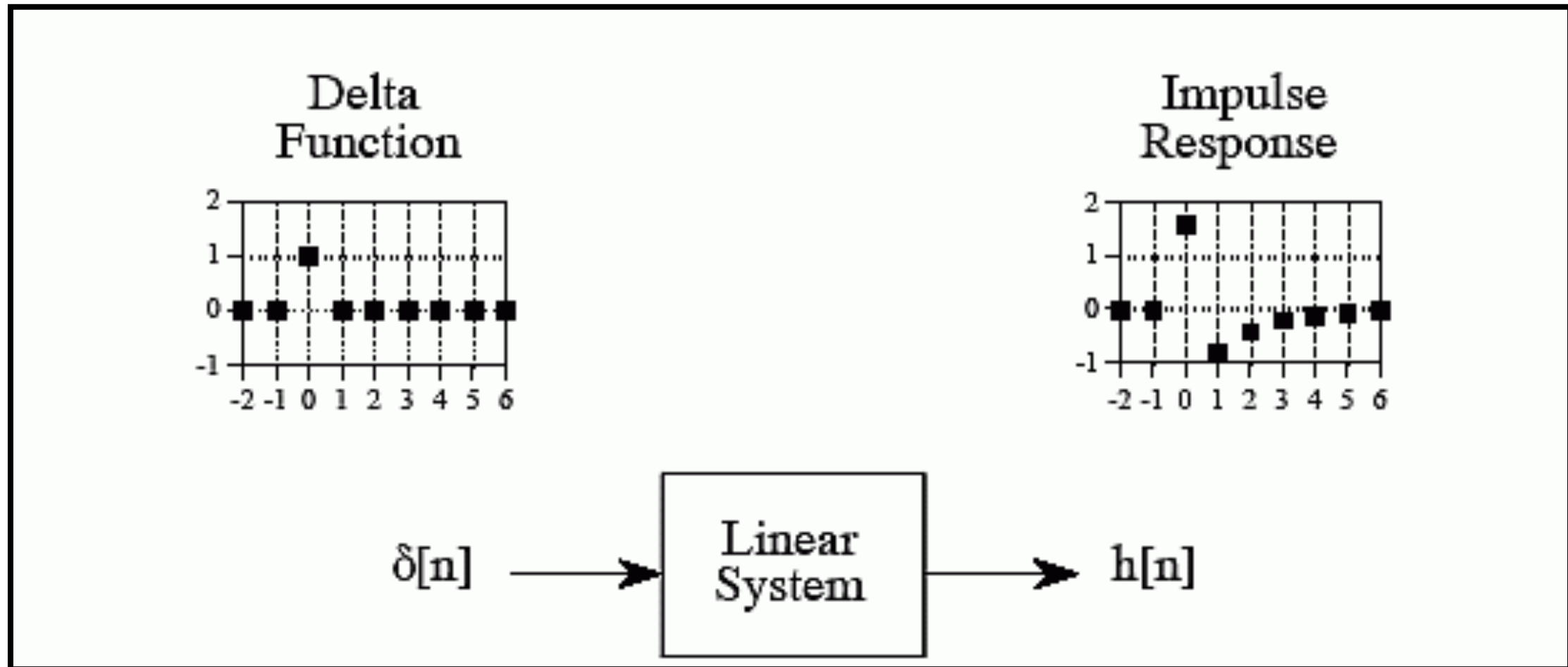


WvD Figure 2.4

Sampling in time is multiplying the continuous time function with a Dirac comb (or delta train), spaced at integer multiples of  $dt$  ( $1/fs$ ).



# Impulse Response Function (IRF)



We know what the system does to a single delta.

We assume the system is LTI.

Therefore, we can reconstruct what the system will do for all signals, as applied to a series of **scaled** and **time-delayed** deltas.



# Impulse Response Function (IRF)



**Input:**  $x(n) = [1, 0, 3, 7, 2, 5]$

**IRF:**  $[2, -1, -1, 0]$

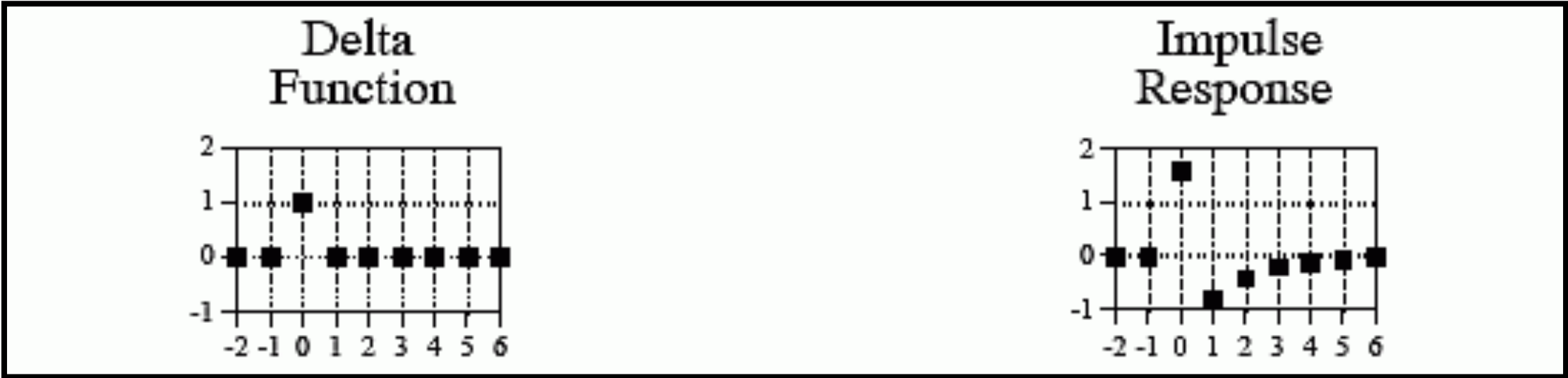
First, deconstruct the signal into a series of scaled & delayed deltas.

Apply the IRF to each delta.

Add the result together.



# Impulse Response Function (IRF)



IRF: [2,-1,-1,0]

Input:  
 $x(n) = [1,0,3,7,2,5]$

n =	0	1	2	3	4	5	6	7	8	9	10
1	2	-1	-1	0	0	0	0	0	0	0	0
0	0	0	0	0	0						
3	0	0	6	-3	-3	0					
7	0	0	0	14	-7	-7	0				
2	0	0	0	0	4	-2	-2	0			
5	0	0	0	0	0	10	-5	-5	0	0	
	2	-1	5	11	-6	1	-7	-5	0	0	0

deltas

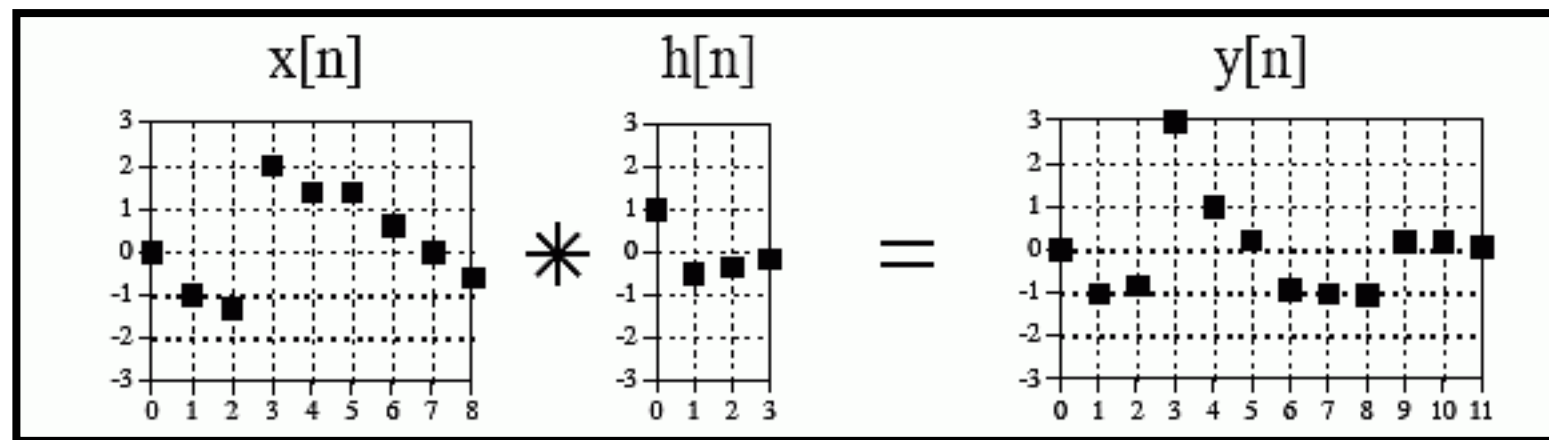




# Convolution

The computation you just performed is called a **convolution**.

The output of a LTI system is the **convolution** of the input signal with the impulse response function, or the signal **convolved** with the IRF.



$$(f * g)(t) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t - \tau) d\tau.$$

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]g[n - m]$$



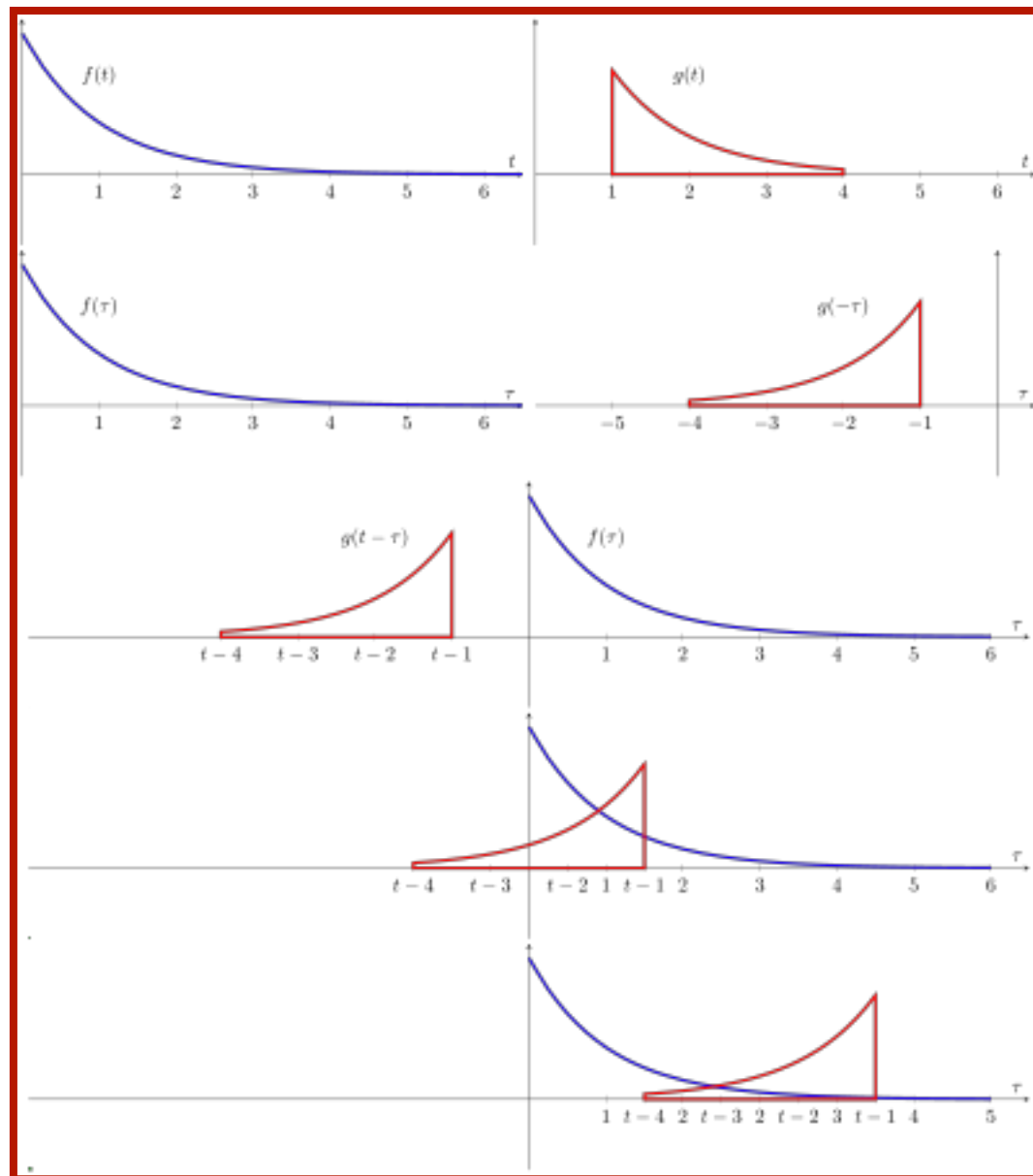
# Convolution

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]g[n - m]$$

**Input:**  $x(n) = [1, 0, 3, 7, 2, 5]$

**IRF:**  $[2, -1, -1, 0]$

**IRF[-n]:**  $[0, -1, -1, 2]$

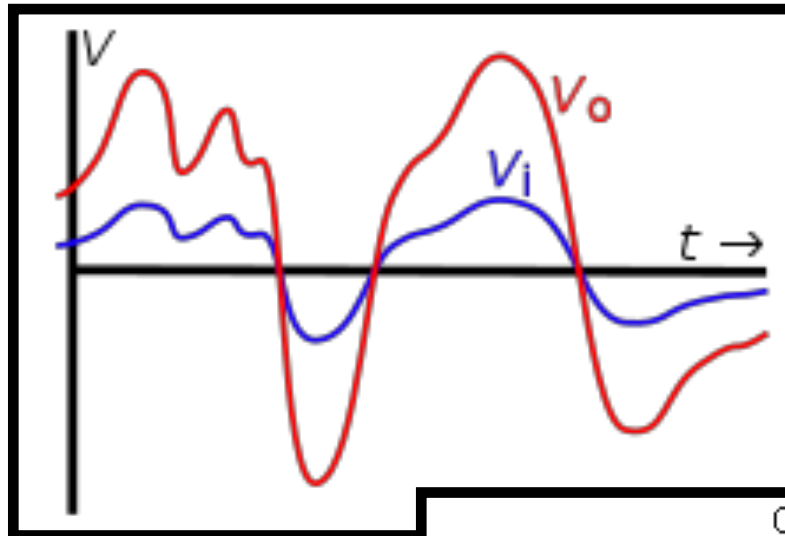


$[0, -1, -1, 2]$	$[1, 0, 3, 7, 2, 5]$	0
$[0, -1, -1, 2]$	$[1, 0, 3, 7, 2, 5]$	2
$[0, -1, -1, 2]$	$[1, 0, 3, 7, 2, 5]$	-1
$[0, -1, -1, 2]$	$[1, 0, 3, 7, 2, 5]$	5
$[0, -1, -1, 2]$	$[1, 0, 3, 7, 2, 5]$	-5

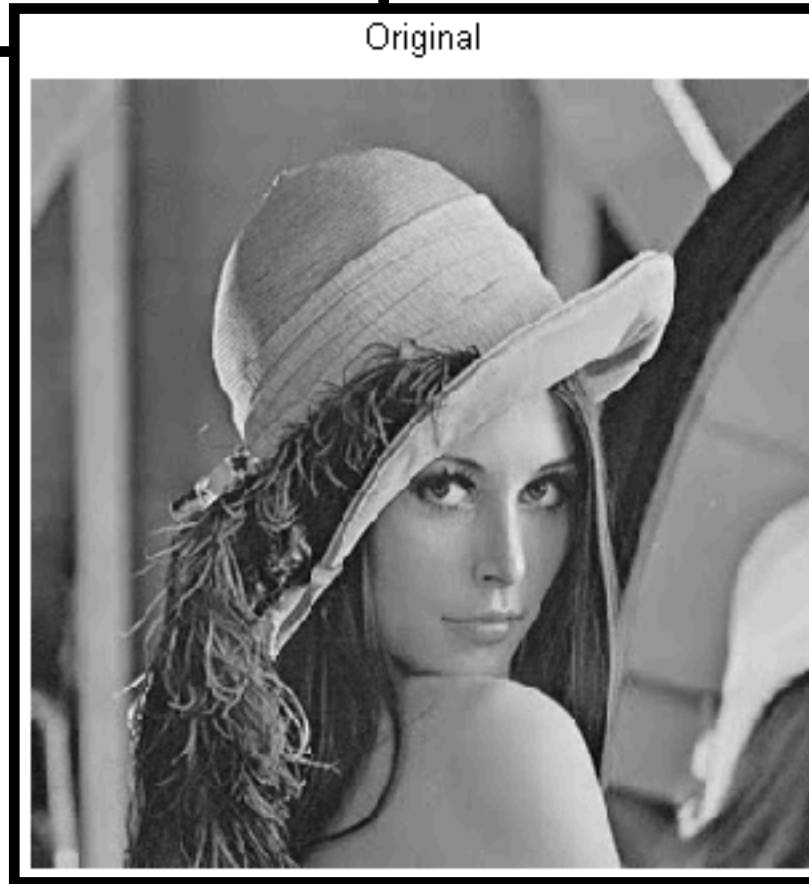


# Convolution In Real Life

## Amplification



## Image Smoothing



## Filtering



1. Formally define LTI systems
2. Convolution & impulse response
3. Introduce the frequency domain



# Foundation of Digital Signal Processing

**Intuition:** we know exactly how your body responds when you eat various fruits, but we have no idea what drinking a smoothie would do. How can we infer your body's response?

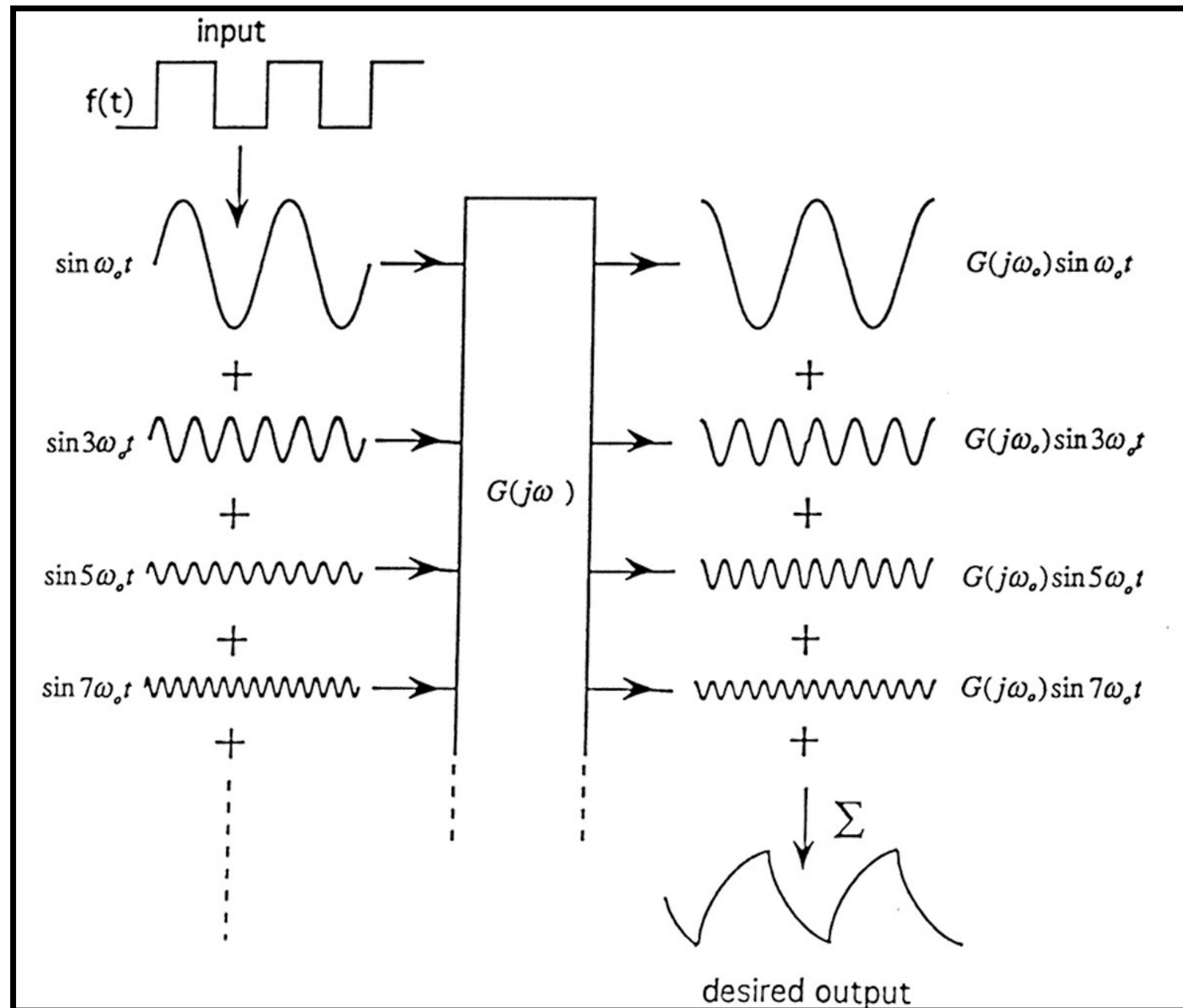
**Digital Signal Processing (DSP):**  
divide (decomposition) and conquer (transformation)

**Impulse Response**

**Frequency Decomposition**

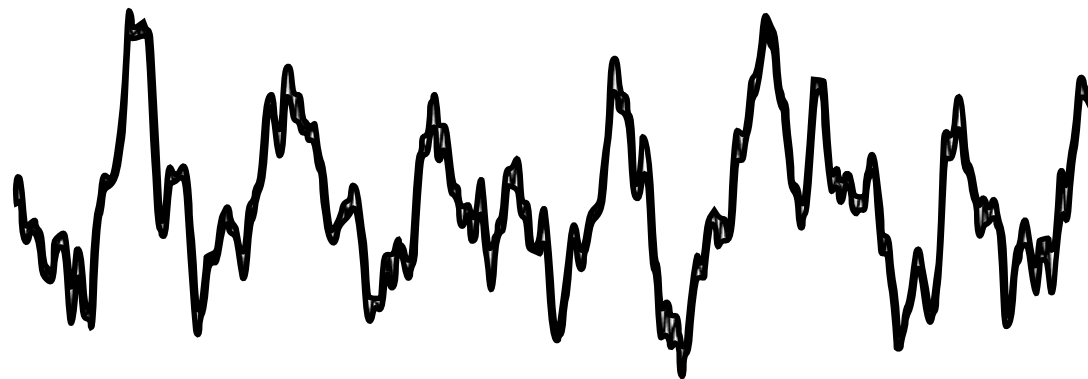


# Frequency Decomposition

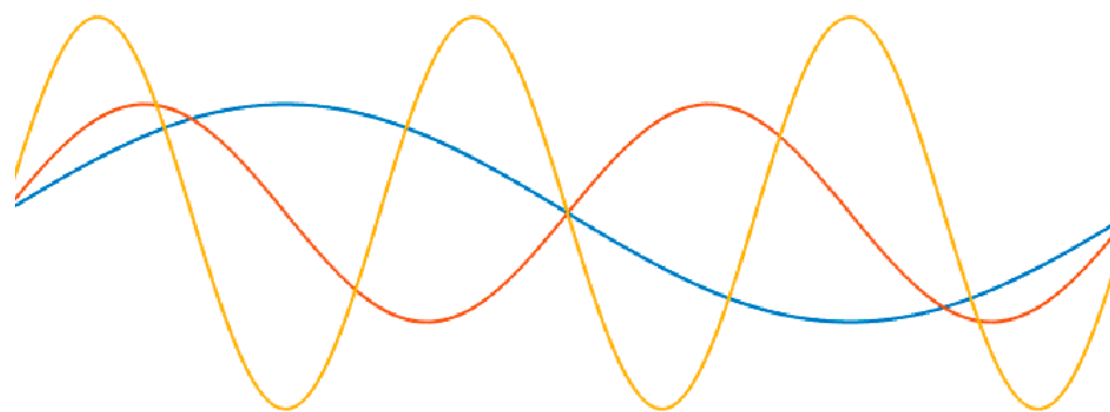


# Frequency Decomposition

Time Domain

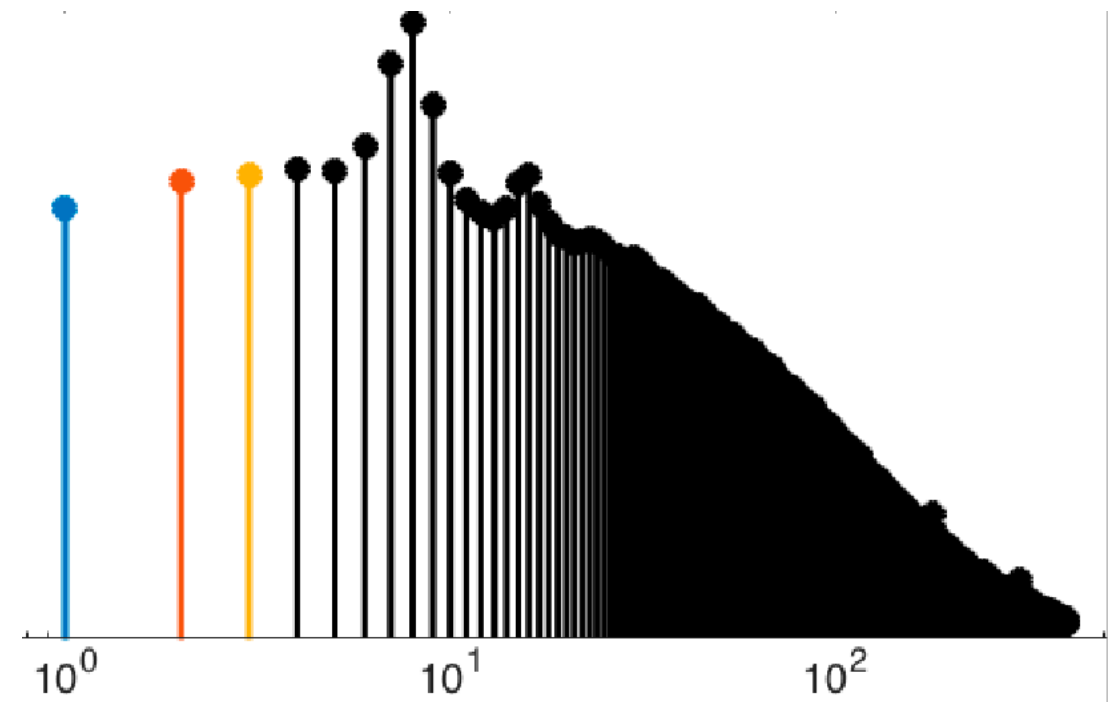


||



time (s)

Frequency Domain



frequency (Hz)



# Convenient Duality

Time  $\longleftrightarrow$  Frequency

Convolution  $\longleftrightarrow$  Multiplication

Sine  $\longleftrightarrow$  Delta

**Hairy!**

**Nice!**





1. Formally define LTI systems
2. Convolution & impulse response
3. Introduce the frequency domain

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

