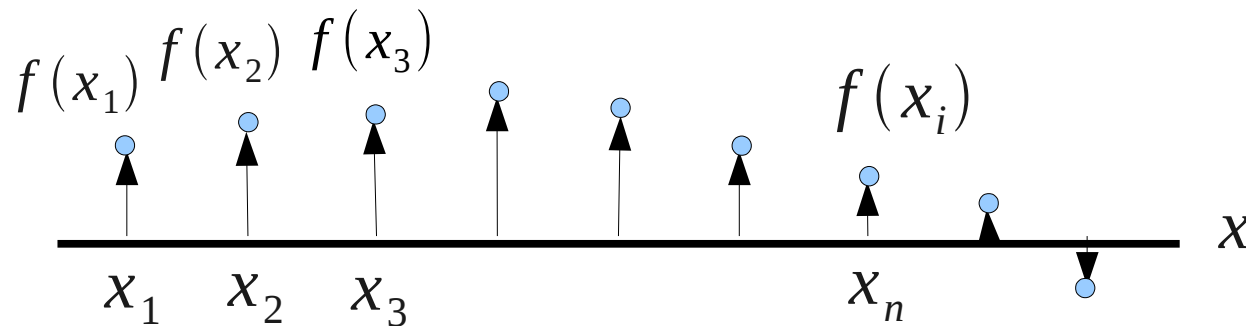


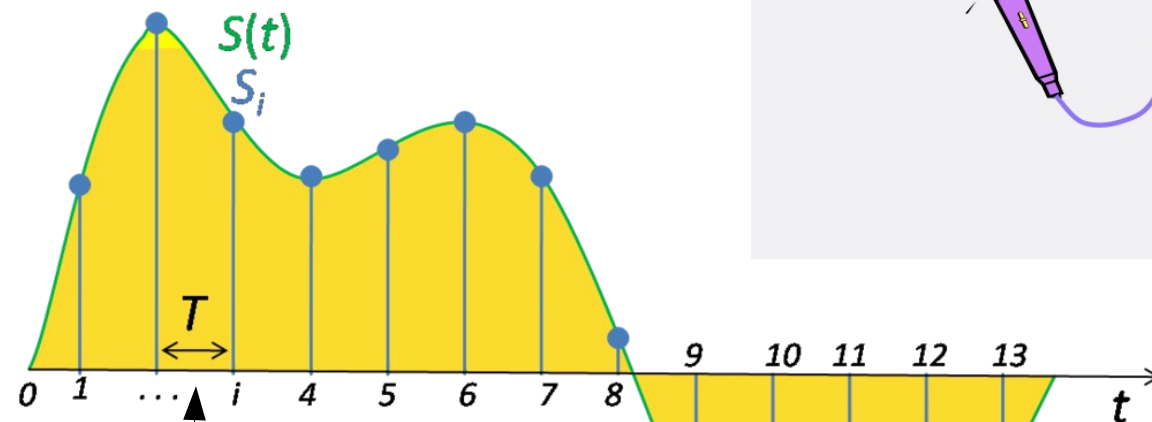
# Sampled data



- Consider continuous function  $f(x)$ .
- Sample the function at regular intervals.
- Sample points  $x_n$
- The result is a vector of values of  $f$ :  
 $[f_1, f_2, f_3, \dots]$

# Example: Digital audio

Sound wave captured by computer



Sample period

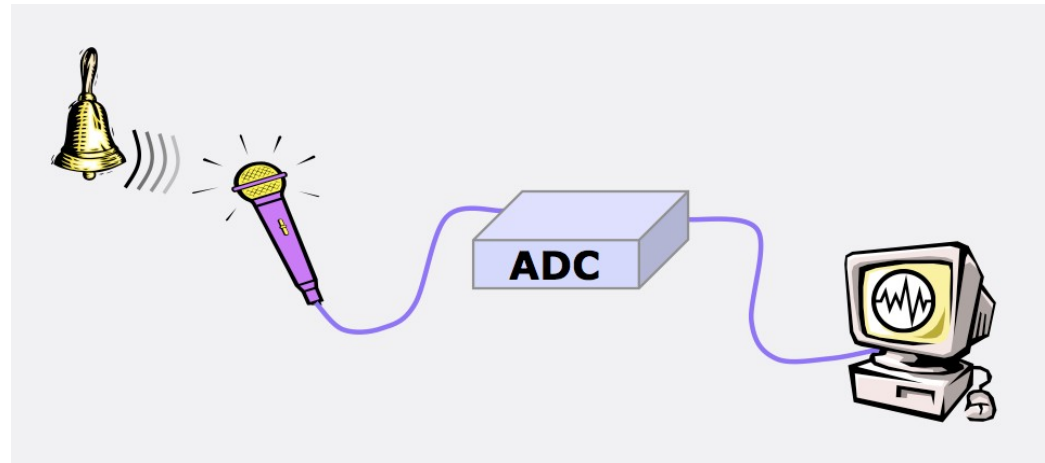
Sample frequency  $f = 1/T$

Sound signal

Sound samples

Sound samples represented as vector of numbers

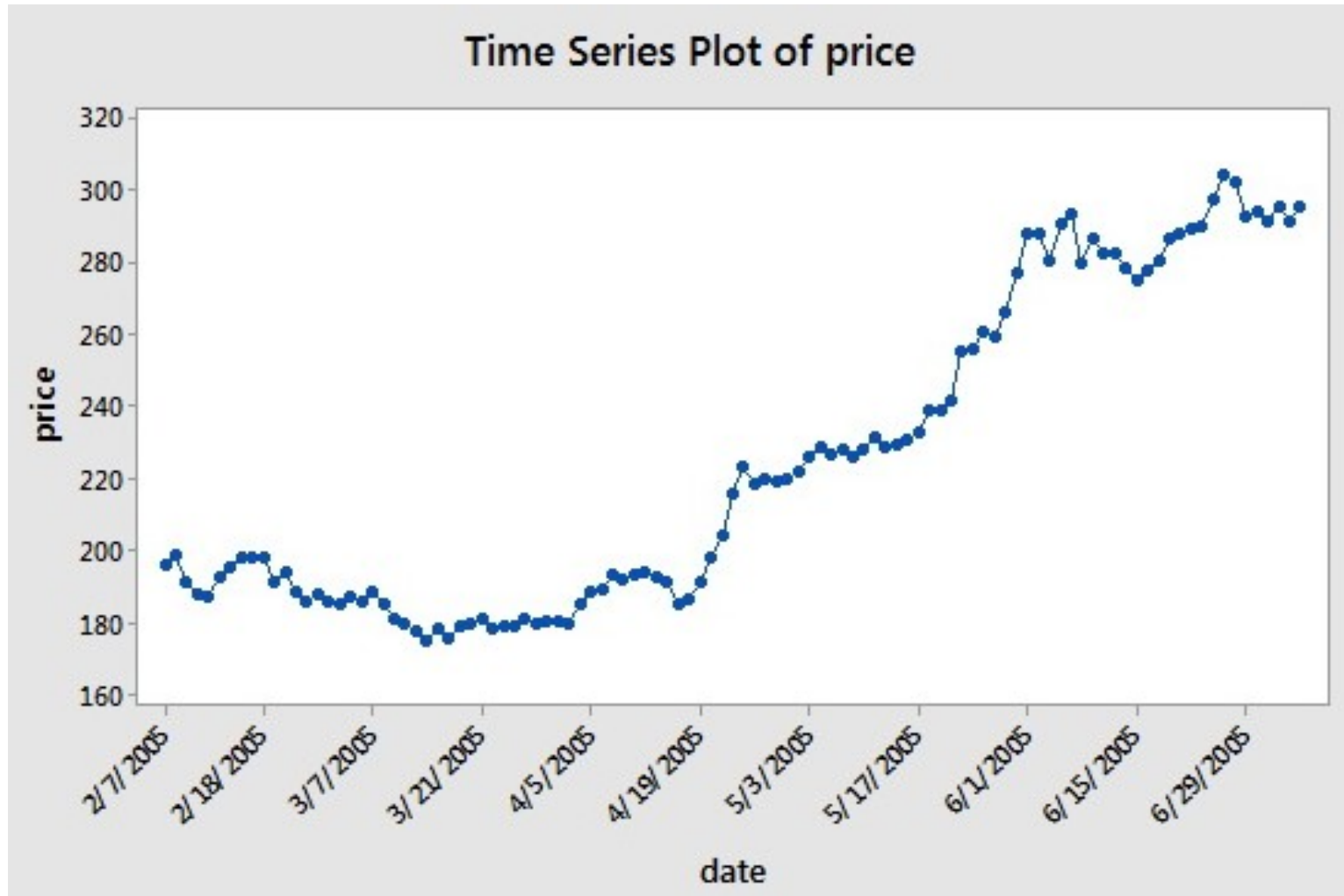
0.3717  
0.6901  
0.9096  
0.9989  
0.9450  
0.7557  
0.4582  
0.0951  
-0.2817  
-0.6182  
-0.8660  
-0.9898  
-0.9718  
-0.8146  
-0.5406  
-0.1893  
0.1893



# Callable function vs. Sampled data function

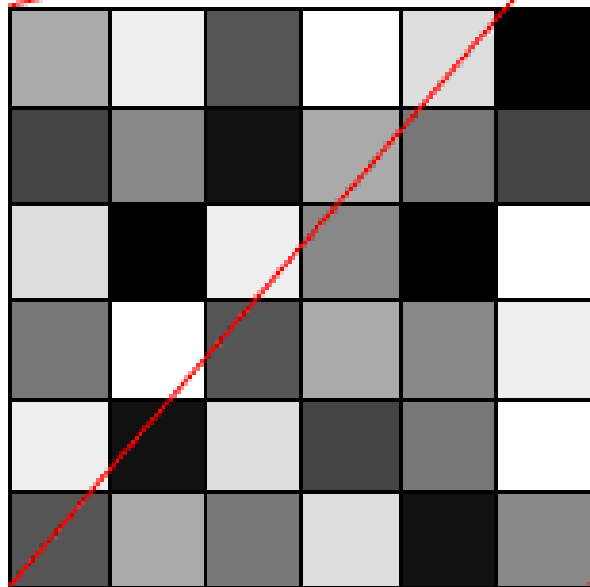
- We usually think of a function as callable.
- Now we need to think of a vector of data as another representation of a function.
- In general, sampling of real data is done using fixed (constant) period.
- For signal vector  $f_n = f(t_n)$ , there is always an implicit time vector  $t_n$  lurking behind the scenes.
- Concept of streaming vs. Batch processing.

# Example: stock prices vs. time



The idea is to treat the data vector as a function which varies in time.

# Example: Digital images (2D)



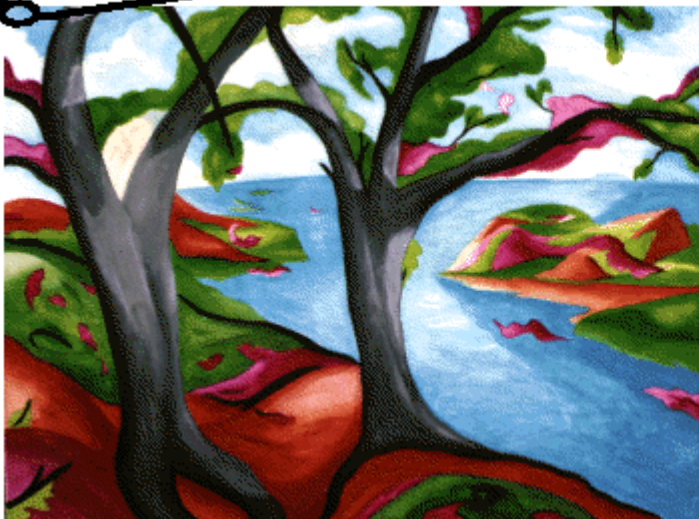
170	238	85	255	221	0
68	136	17	170	119	68
221	0	238	136	0	255
119	255	85	170	136	238
238	17	221	68	119	255
85	170	119	221	17	136

B&W image  
stored as matrix  
of “pixels” --  
numbers  
signifying  
black/white level  
at each point.

# Color images

Color image stored as three matrices of “pixels” -- numbers signifying intensity level at each point.

0.2235	0.1294	<b>Blue</b>	0.4196	0.2235	0.2588	0.2588
0.5804	0.2902	<b>0.0627</b>	0.2902	0.2902	0.4824	0.2235
0.5804	0.0627	0.0627	0.0627	0.2235	0.2588	0.2588
0.5176	0.1922	0.0627	<b>Green</b>	0.1922	0.2588	0.2588
0.5176	0.1294	<b>0.1608</b>	0.1294	0.1294	0.2588	0.2588
0.5176	0.1608	0.0627	0.1608	0.1922	0.2588	0.2588
0.5490	0.2235	0.5490	<b>Red</b>	0.7412	0.7765	0.7765
0.490	0.3882	<b>0.5176</b>	0.5804	0.5804	0.7765	0.7765
0.2235	0.2588	0.2902	0.2588	0.2235	0.4824	0.2235
0.2235	0.1608	0.2588	0.2588	0.1608	0.2588	0.2588
0.2235	0.1608	0.2588	0.2588	0.2588	0.2588	0.2588



Most commonly, the three matrices correspond to levels of Red, Green, and Blue (RGB).

The three matrices are sometimes called “color planes”



# Numerical derivatives and sampled data

- Use Taylor's series to derive:
  - Forward difference
  - Backward difference
  - Two-sided difference (symmetric difference)
- Note truncation error from each

# Computing the first derivative

- Derive on blackboard:

- Forward difference

$$\left. \frac{df}{dx} \right|_x = \frac{f(x+h) - f(x)}{h} - \frac{h}{2} f''(x) - \frac{h^2}{6} f'''(x) + \dots$$

Drop

- Backward difference

$$\left. \frac{df}{dx} \right|_x = \frac{f(x) - f(x-h)}{h} - \frac{h}{2} f''(x) + \frac{h^2}{6} f'''(x) + \dots$$

Drop

- Two-sided difference

$$\left. \frac{df}{dx} \right|_x = \frac{f(x+h) - f(x-h)}{2h} - \frac{h^2}{6} f'''(x) + \dots$$

Drop



# Approximations using more points

**Table 1.** Compact central differencing formulas for the first derivative,  $f_0^I$ , with the leading term of its systematic error, for  $j = 3(2)17$ , where the number of data points  $j$  listed in the first column includes  $f_0$ . The term *compact* indicates use of the smallest possible number  $j$  of equidistant data. The results shown in tables 1 through 4 were computed with the spreadsheet approach illustrated in section 9.2.5 of ref. 6. For  $j > 9$  this required higher-precision matrix inversion to get sufficiently accurate answers, for which we used Volpi's BigMatrix freeware, see ref. 6 section 11.9.

$j$	Formula for $f_0^I$	Leading term of systematic error
3	$(-f_{-1} + f_1)/(2\delta)$	$-f^{III} \delta^2/6$
5	$(f_{-2} - 8f_{-1} + 8f_1 - f_2)/(12\delta)$	$+f^V \delta^4/30$
7	$(-f_{-3} + 9f_{-2} - 45f_{-1} + 45f_1 - 9f_2 + f_3)/(60\delta)$	$-f^{VII} \delta^6/140$
9	$(3f_{-4} - 32f_{-3} + 168f_{-2} - 672f_{-1} + 672f_1 - 168f_2 + 32f_3 - 3f_4)/(840\delta)$	$+f^{IX} \delta^8/630$
11	$(-2f_{-5} + 25f_{-4} - 150f_{-3} + 600f_{-2} - 2100f_{-1} + 2100f_1 - 600f_2 + 150f_3 - 25f_4 + 2f_5)/(2520\delta)$	$+f^{XI} \delta^{10}/2772$
13	$(5f_{-6} - 72f_{-5} + 495f_{-4} + 2200f_{-3} + 7425f_{-2} - 23760f_{-1} + 23760f_1 - 7425f_2 + 2200f_3 - 495f_4 + 72f_5 - 5f_6)/(27720\delta)$	$+f^{XIII} \delta^{12}/12012$
15	$(-15f_{-7} + 245f_{-6} - 1911f_{-5} + 9555f_{-4} - 35035f_{-3} + 105105f_{-2} - 315315f_{-1} + 315315f_1 - 105105f_2 + 35035f_3 - 9555f_4 + 1911f_5 - 245f_6 + 15f_7)/(360360\delta)$	$+f^{XV} \delta^{14}/51480$
17	$(7f_{-8} - 128f_{-7} + 1120f_{-6} - 6272f_{-5} + 25480f_{-4} - 81536f_{-3} + 224224f_{-2} - 640640f_{-1} + 640640f_1 - 224224f_2 + 81536f_3 - 25480f_4 + 6272f_5 - 1120f_6 + 128f_7 - 7f_8)/(720720\delta)$	$+f^{XVII} \delta^{16}/218790$

**An improved numerical approximation for the first derivative<sup>†</sup>**

ROBERT DE LEVIE

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*J. Chem. Sci.*, Vol. 121, No. 5, September 2009, pp. 935–950.

# Second derivative

- Derived on blackboard

$$\left. \frac{d^2 f}{dx^2} \right|_x = \frac{f(x+h) - 2f(x) + f(x-h)}{h^2} + \frac{h^2}{12} f^{(4)}(x) + \dots$$

Drop



- Truncation error is of order  $h^2$

# What h to use?

$$h = \sqrt{\epsilon(f(x))}$$

- Use Taylor's series
- Show truncation and round-off error
- Minimize total error to find optimal h.
- Derivation on blackboard
- Recommended values (one sided derivative):
  - If using doubles, and  $f(x)$  is near 1, use  $h = 1e-8$
  - If using singles and  $f(x)$  is near 1, use  $h = 3e-4$ .

# Demonstration

- Loop over  $h$  values
- Compute finite-difference derivative of  $y_c = \sin(x)$  for a bunch of random  $x$  values using this  $h$  value.
- Compute analytic derivative  $y_t = \cos(x)$ .
- Compute average error  $\text{mean}(y_t - y_c)$  over different random  $x$  values.
- At end of loop, plot error vs.  $h$ .

```

function [h_vec, err_vec] = test_derivative()
    start = -15;    % Start at 1e-15
    stop = 0;      % Stop at 1e0

    % Vector of h values to test
    h_vec = logspace(start, stop, 200);
    h_length = length(h_vec);

    % Pre-initialize error vector which will get filled in below.
    err_vec = zeros(1, h_length);

    % This is number of times to generate random x and compute
    % numerical derivative at that point to create average error.
    Nsamples = 50;

    % Main loop -- compute average error for each value of h in h_vec.
    for h_idx = 1:h_length
        h = h_vec(h_idx);

        % Create a row vector of random x values
        x = 1*randn(1, Nsamples);
        computed = derivative(@sin, x, h);
        true = cos(x);
        err = mean(computed-true);

        err_vec(h_idx) = err/Nsamples;
    end

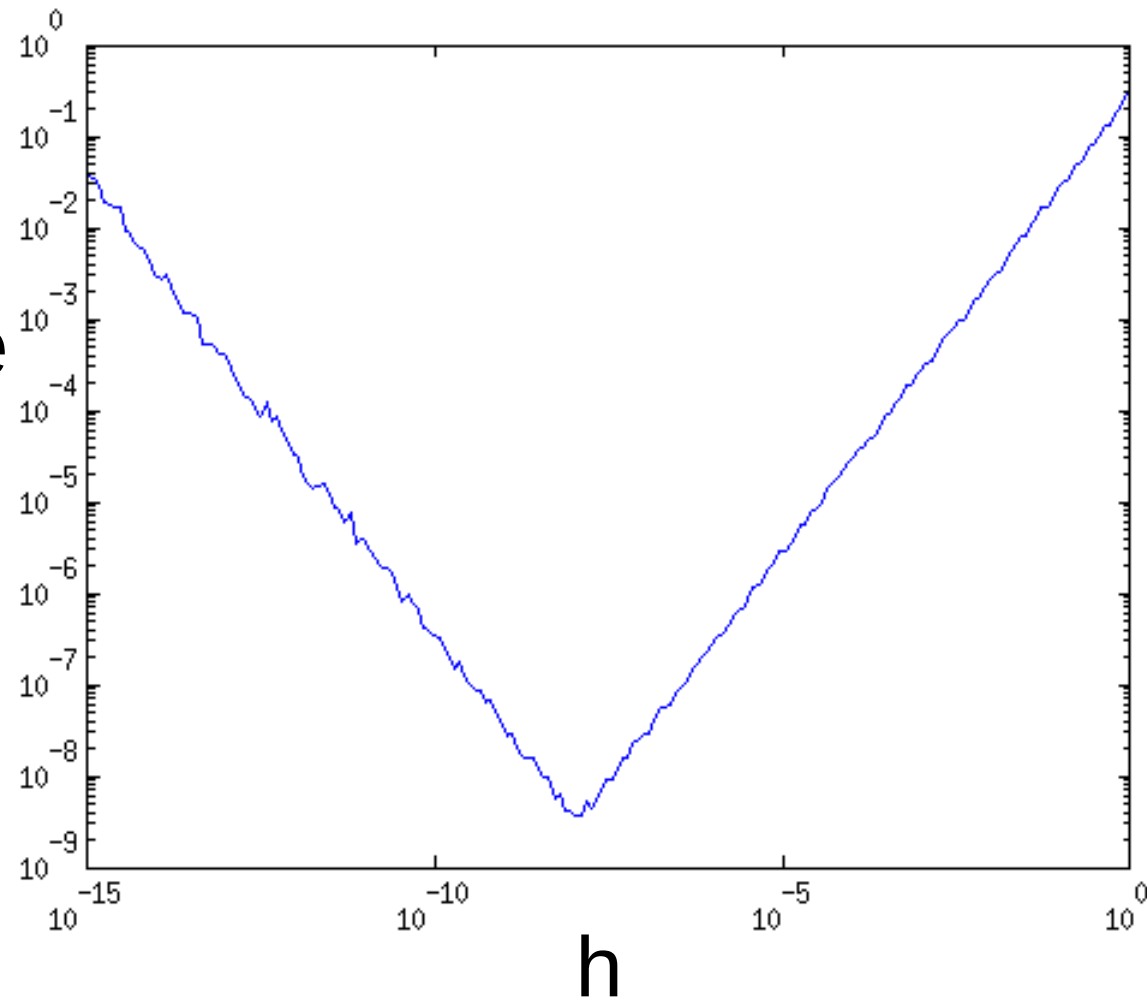
    % plot results.
    loglog(h_vec, abs(err_vec))

end

```

# One sided derivative

Absolute  
Error

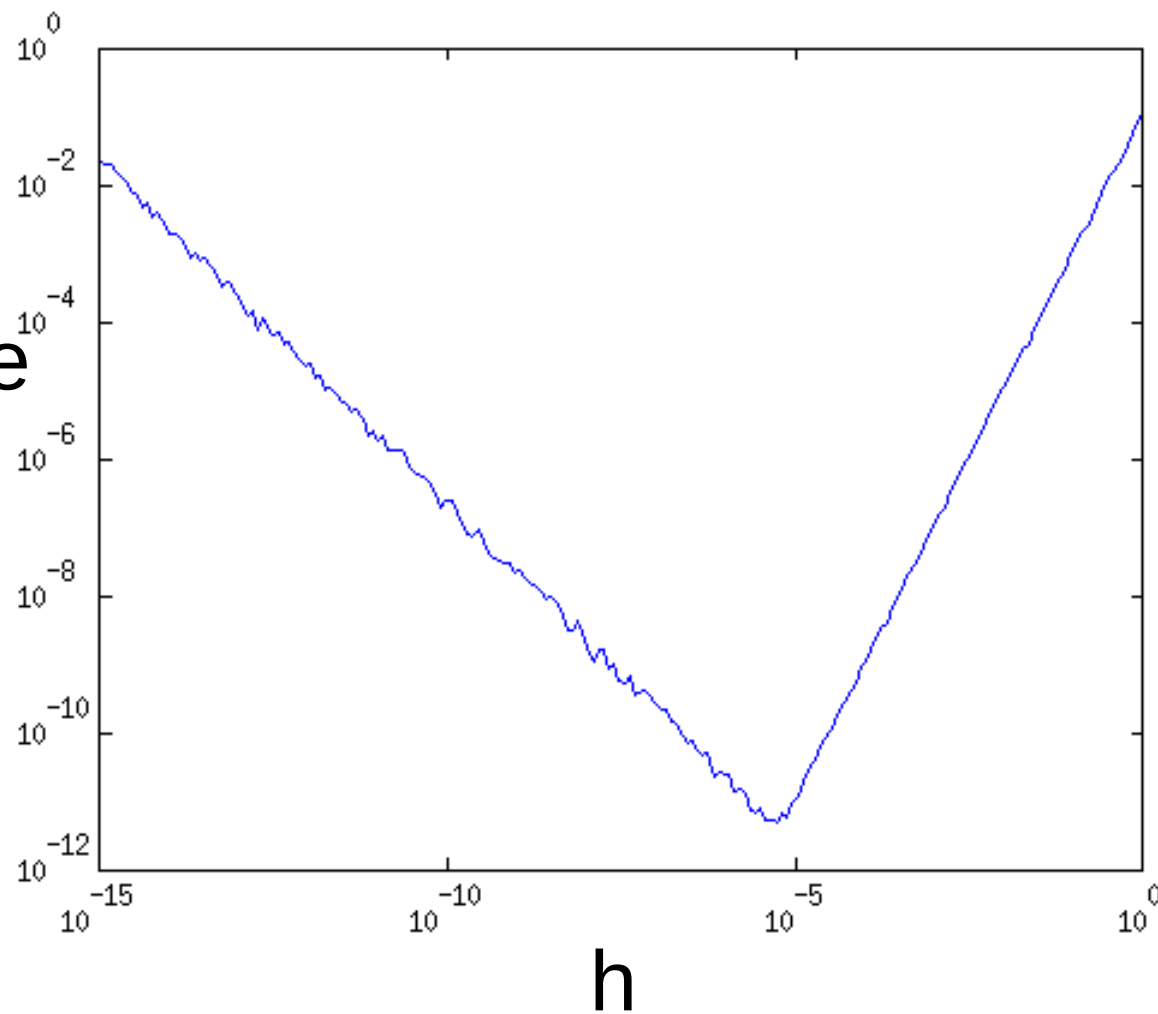


If using doubles, and  $f(x)$  is near 1, use  $h = 1e-8$



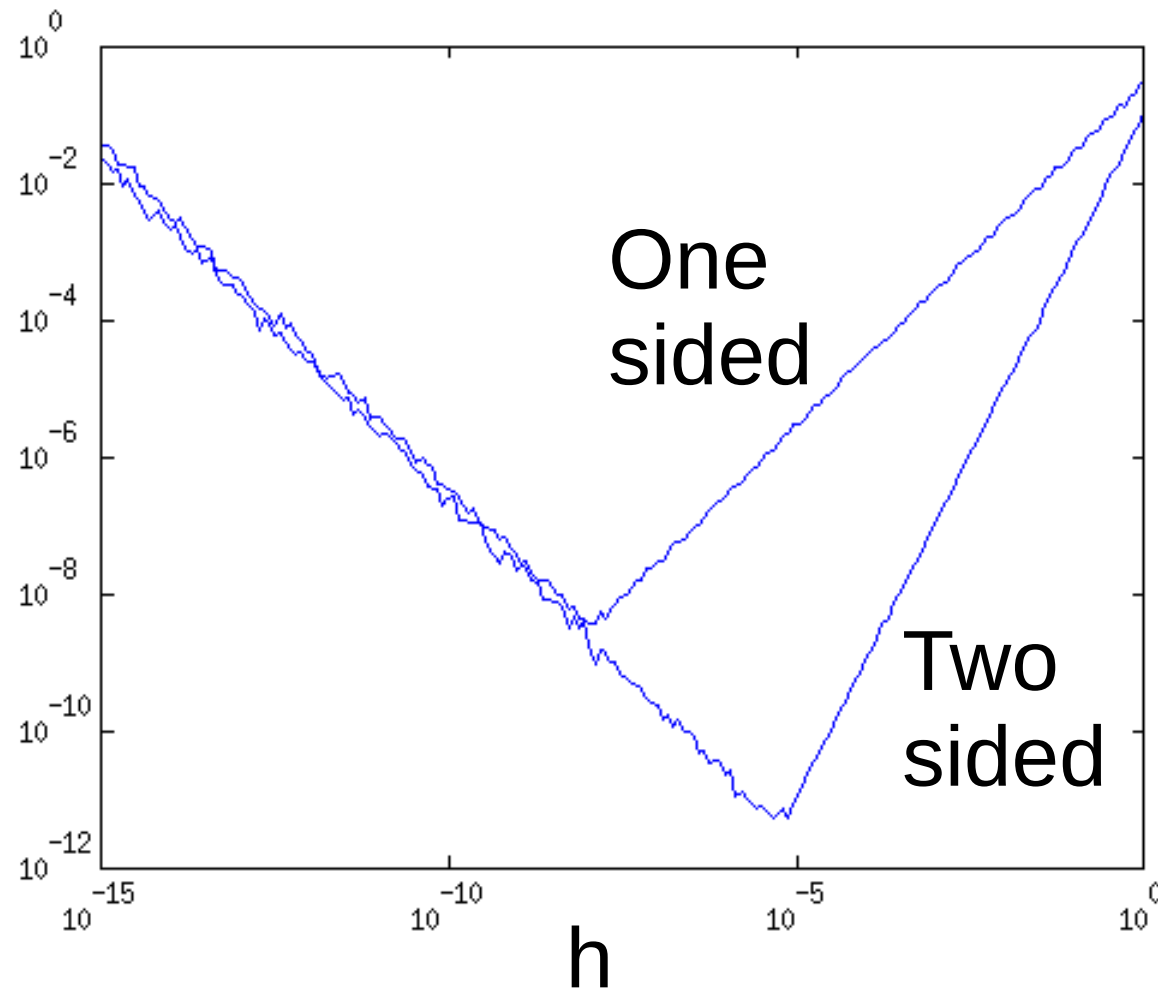
# Two sided derivative

Absolute  
Error



# Both plots together

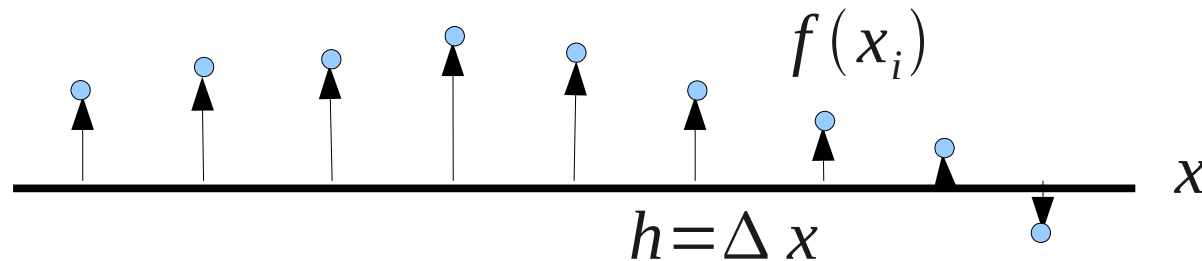
Absolute  
Error



# Demonstration

- Look at Matlab code in /home/sdb/Northeastern/Class2:
  - derivative.m
  - test\_derivative.m
- To run it, do this:
  - `[x, y] = test_derivative()`

# Derivatives as Matrix Multiplications



- $f(x)$  is a vector of values evaluated at each  $x_i$ :  $[f_0, f_1, f_2, f_3, \dots]$

- Derivative (one-sided):  $\frac{1}{h}[f_1 - f_0, f_2 - f_1, f_3 - f_2, \dots]$

$$\frac{\partial f}{\partial x} = \frac{1}{h} \begin{pmatrix} -1 & 1 & 0 & 0 & \dots \\ 0 & -1 & 1 & 0 & \dots \\ 0 & 0 & -1 & 1 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix} \begin{pmatrix} f_0 \\ f_1 \\ f_2 \\ f_3 \\ \vdots \end{pmatrix}$$

# Second derivative

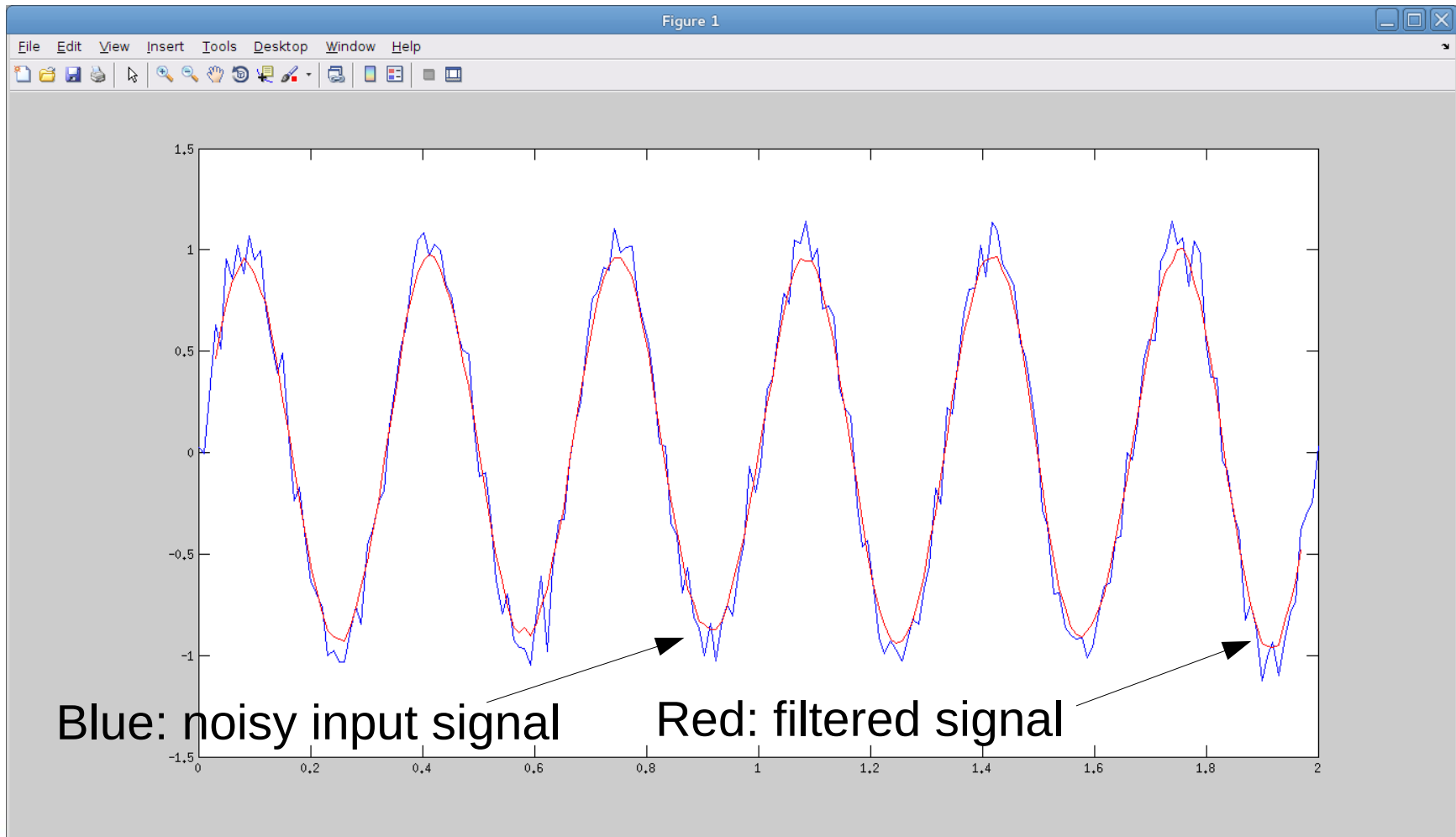
$$\frac{\partial^2 f}{\partial x^2} = \frac{1}{2h} \begin{pmatrix} -2 & 1 & 0 & 0 & \cdots \\ 1 & -2 & 1 & 0 & \cdots \\ 0 & 1 & -2 & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix} \begin{pmatrix} f_0 \\ f_1 \\ f_2 \\ f_3 \\ \vdots \end{pmatrix}$$

$$\frac{1}{2h} [f_1 - 2f_0, f_2 - 2f_1 + f_0, f_3 - 2f_2 + f_1, \cdots]$$

- We will see this again ....
- Note issue with boundary.
- A matrix is a linear operator.

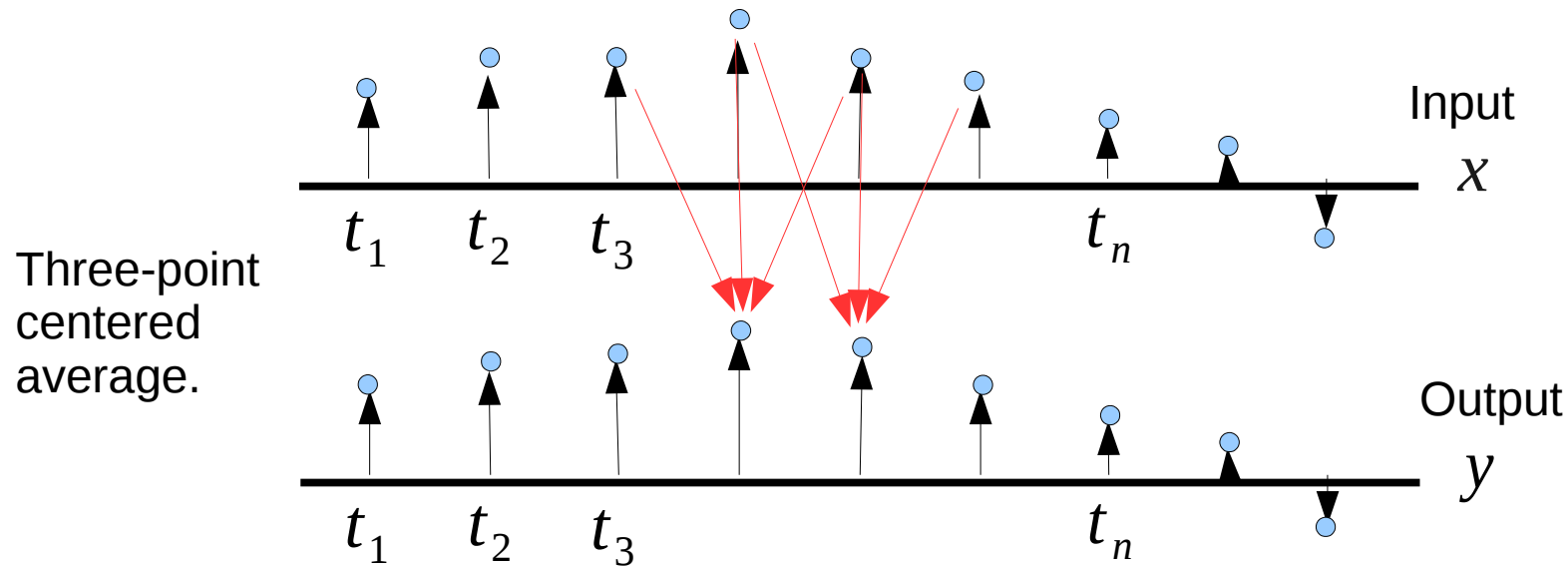
# Next topic: Filtering of data

- Input: Noisy data ← Imagine an audio stream (music)
- Desired output: Data with noise removed.





# Simplest filter: moving box average



- Idea: Take average of surrounding samples. Do this for each sample.

$$y_n = \frac{x_{n-1} + x_n + x_{n+1}}{3}$$

- The hardest part is getting the index arithmetic right....

```

function [tf, yf] = box_filter_centered(t, x, Npts)
    % Performs centered box average over Npts points.

    % Check that Npts is an odd number
    if (mod(Npts, 2) == 0)
        error('Npts must be an odd number!')
    end

    % Compute number of points to the left & right
    Noffset = (Npts-1)/2;

    Nx = length(x)
    yf = zeros(Nx-Npts+1, 1);
    tf = zeros(Nx-Npts+1, 1);

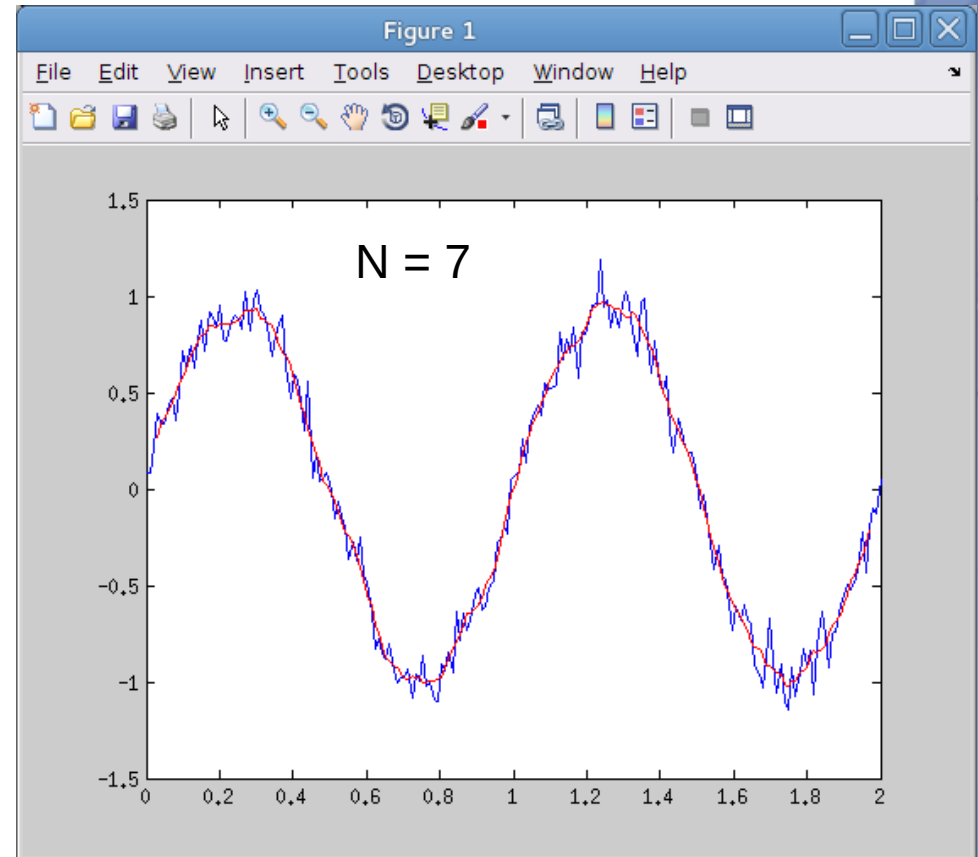
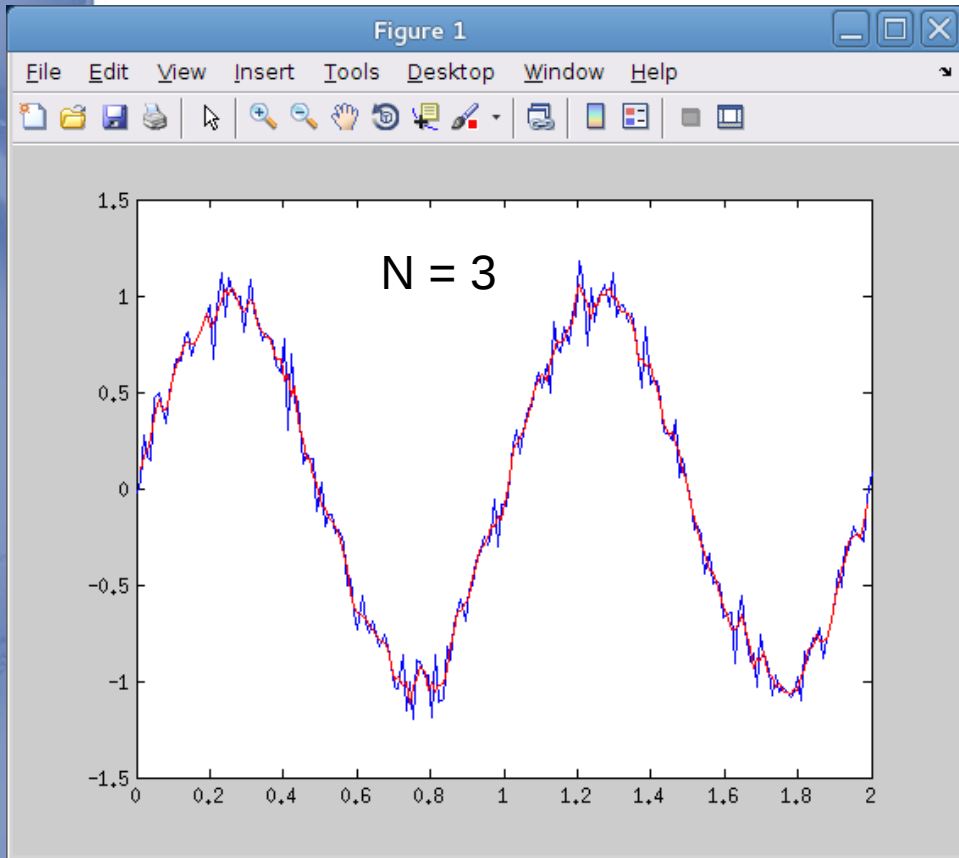
    % Loop over input pts, compute box average
    for n = (1+Noffset):(Nx-Noffset)
        idx = (n-Noffset):(n+Noffset);
        tf(n-Noffset) = t(n);
        yf(n-Noffset) = sum(x(idx))/Npts;
    end
end

```

Note that I create  
a new time series  
vector along with  
the signal vector.

Here's where we  
compute the  
average of the  
input signal

# Effect of different Npts



- Averaging more points together -> less noise in signal.

# Some remarks

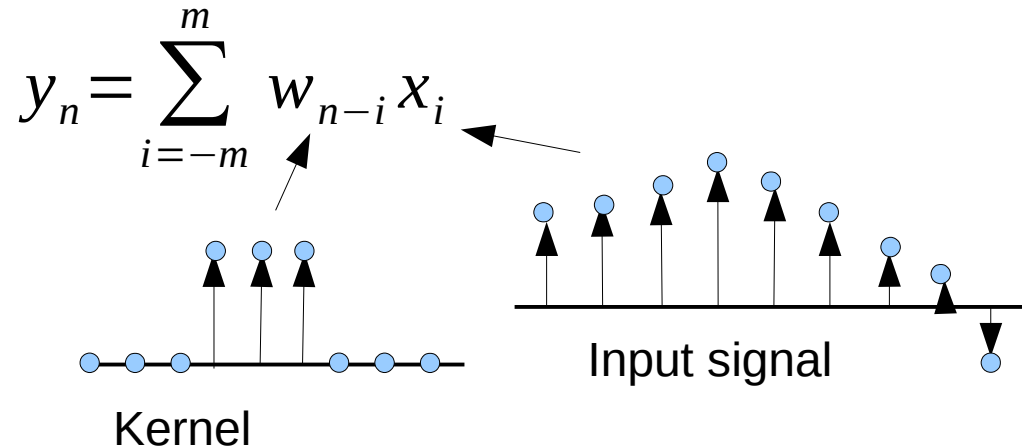
- The general computation is

$$y_n = \sum_{i=-m}^m w_{n-i} x_i$$

Convolution –  
Remember this  
expression!

- Coefficients  $w_n$  must sum to 1 (to preserve “energy” in signal).
- How to deal with points at end?
- Concept: causal vs. non-causal filters
  - Centered average filter is non-causal.

# Filter kernels



- Regard  $w$  coefficients as a function.
  - That function is called the “kernel”.
- Different kernels give different filter characteristics. (Recall effect of different Npts.)

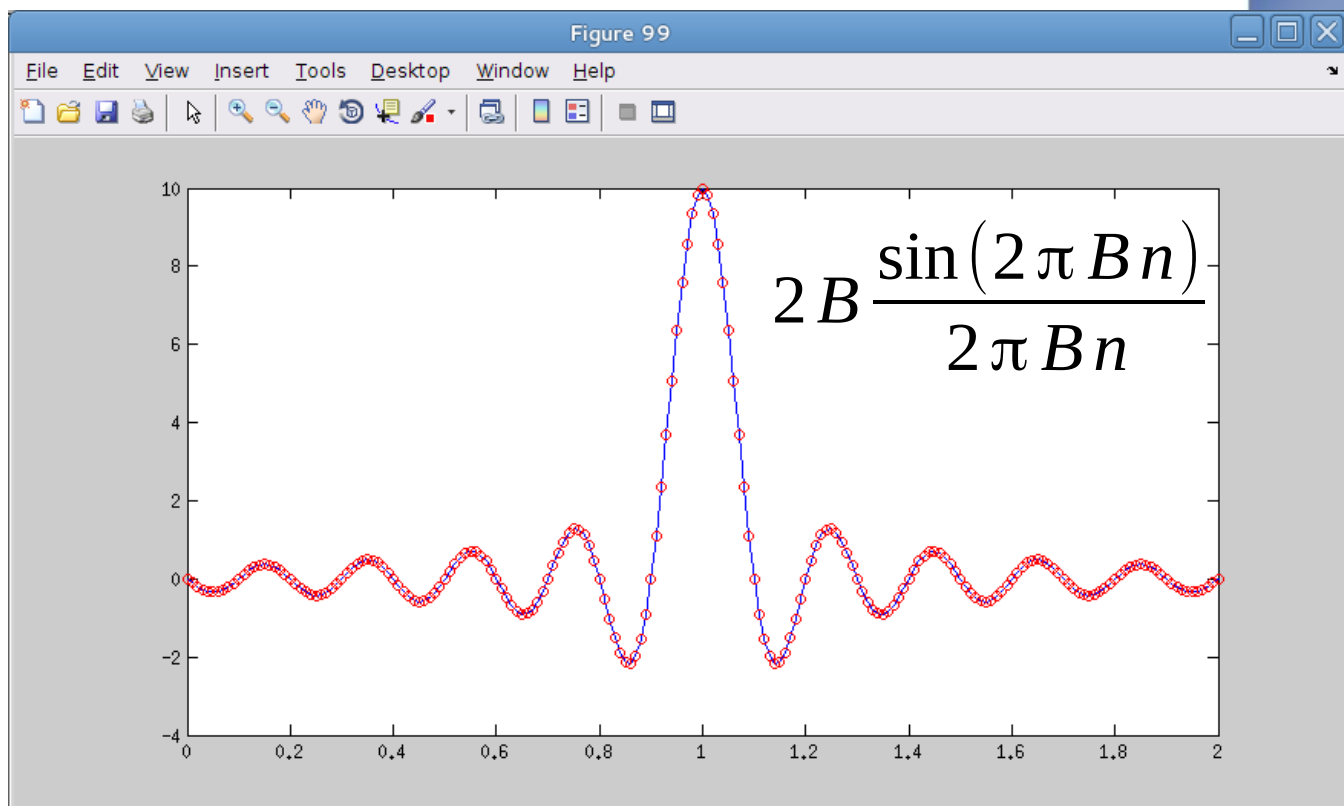
# Example: Sinc kernel

- Consider function  $\text{sinc}(x) = \sin(x)/x$

- Use as kernel in filter:

$$y_n = \sum_{i=-m}^m w_{n-i} x_i$$

- Why use this crazy function?



→ To be revealed in session 2



```

function yf = sinc_filter_centered(t, x, B)
    % Filters x using sinc kernel. The desired filter bandwidth
    % (cut-off freq) is B. We apply the filter to a cyclic
    % version of the input signal. That is, we assume the input
    % x(t) is periodic, and the input vector contains one period of x.

    % For everything to work, we require length(t) to be odd.
    N = length(t);
    if (mod(N, 2) == 0)
        error('length(t) must be odd!')
    end

    % Create filter kernel
    Tmax = t(end);
    w = 2*B*sinc(2*B*(t-Tmax/2));
    % Now shift it 1/2 around
    w = circshift(w, [0, (N-1)/2]);

    figure(99)
    plot(t, w);
    hold on
    plot(t, w, 'ro');

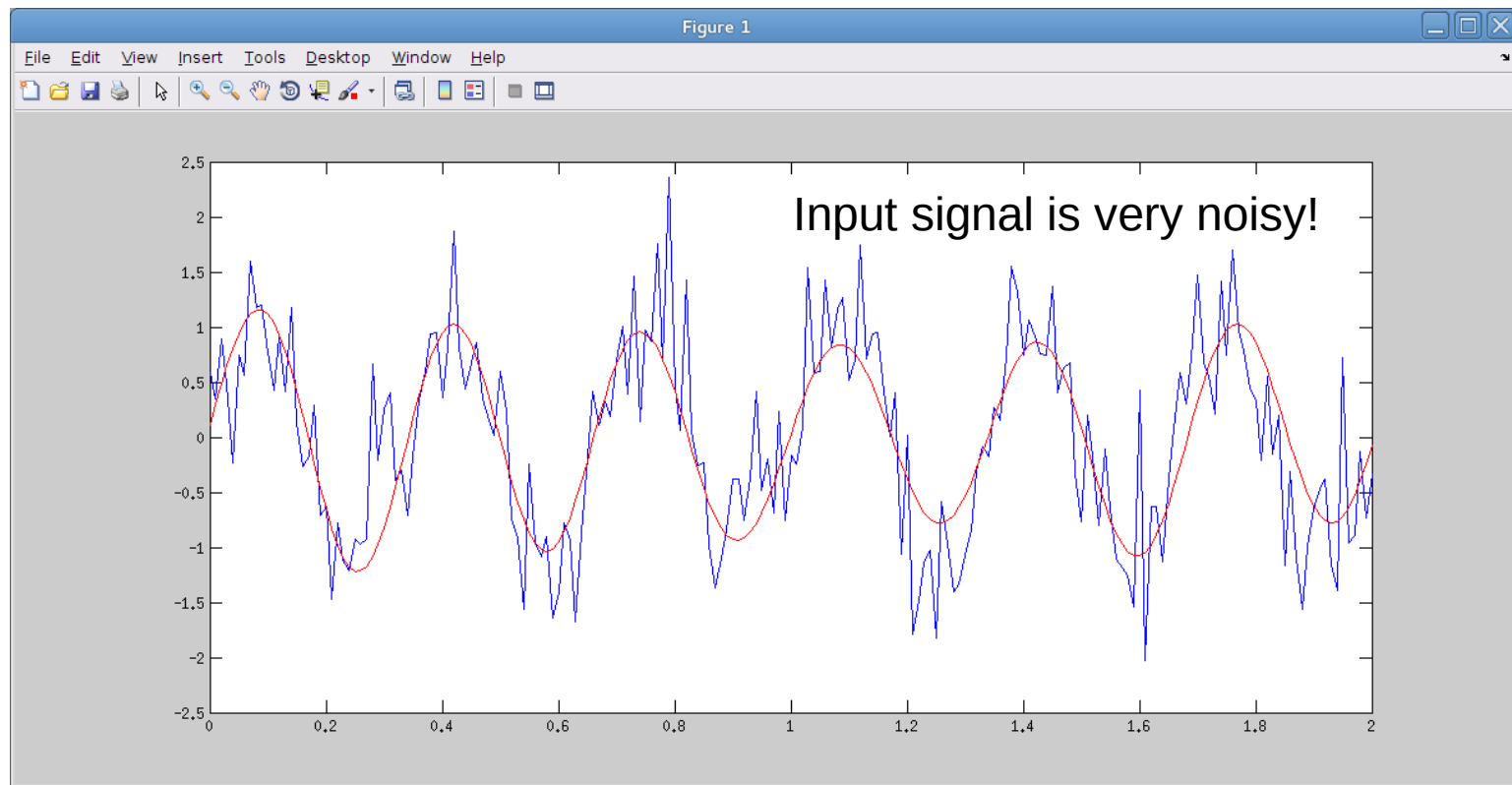
    % Create index used in computation
    idx = 1:N;

    % Loop over input pts, compute filtered signal
    for i = 1:N
        j = circshift(idx, [0, i-1]);
        yf(i) = dot(x(idx), w(j))/(N/2);
    end

end
end

```

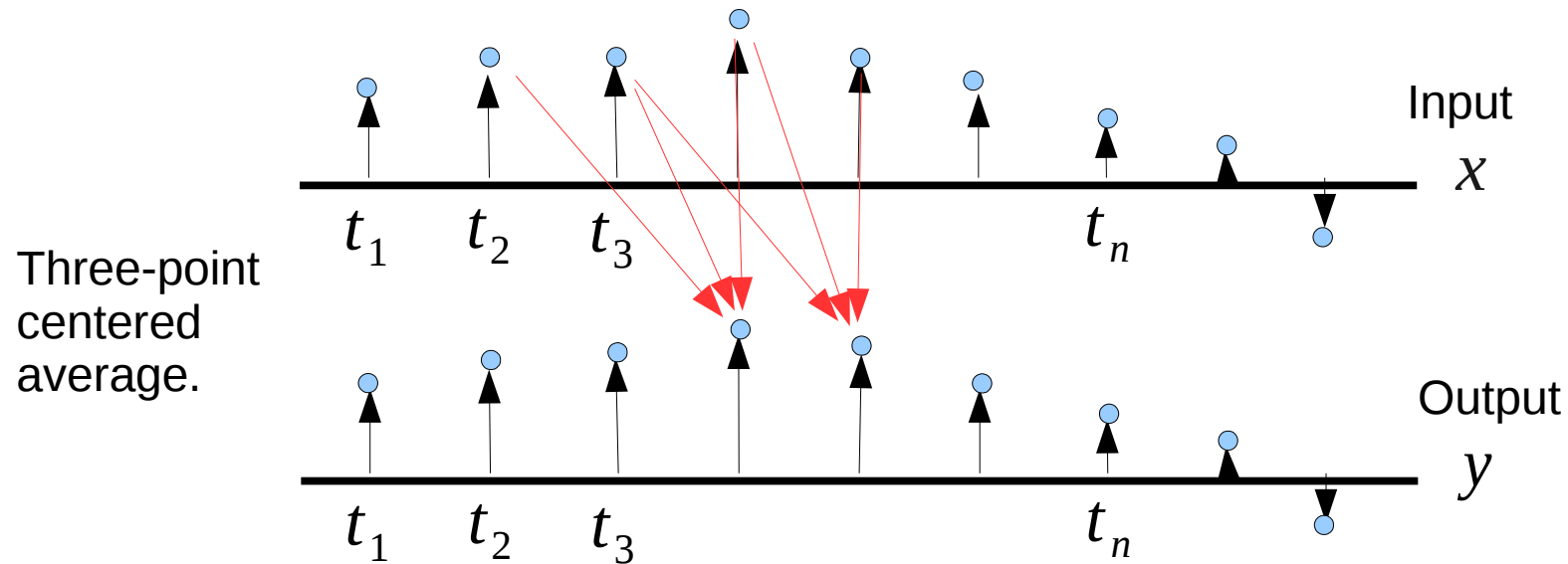
# Filtered signal



$$f_0 = 3 \text{ Hz} \quad B = 4 \text{ Hz} \quad A_n = 0.5$$

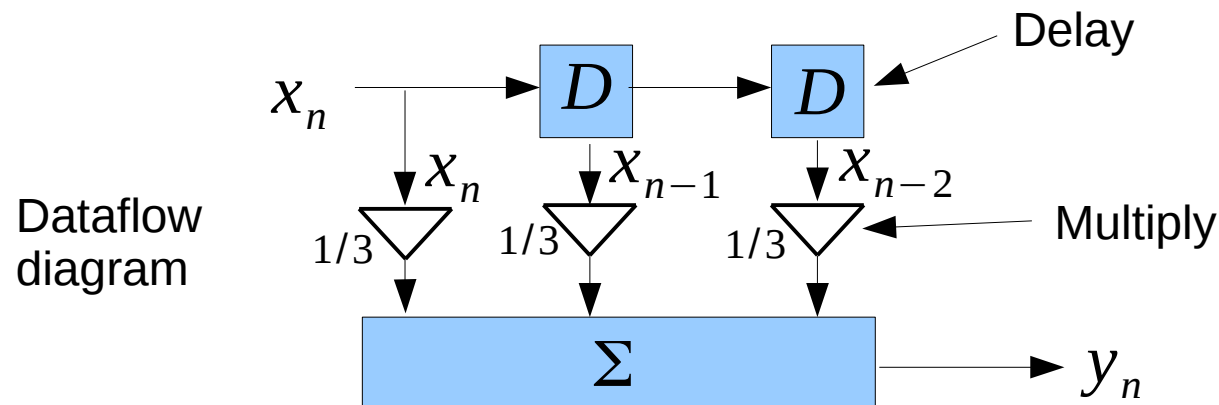
- Sinc() is applied to cyclic copies of input signal to deal with question of signal ends.
- Noise is very successfully reduced.

# Causal filter (trailing box average)

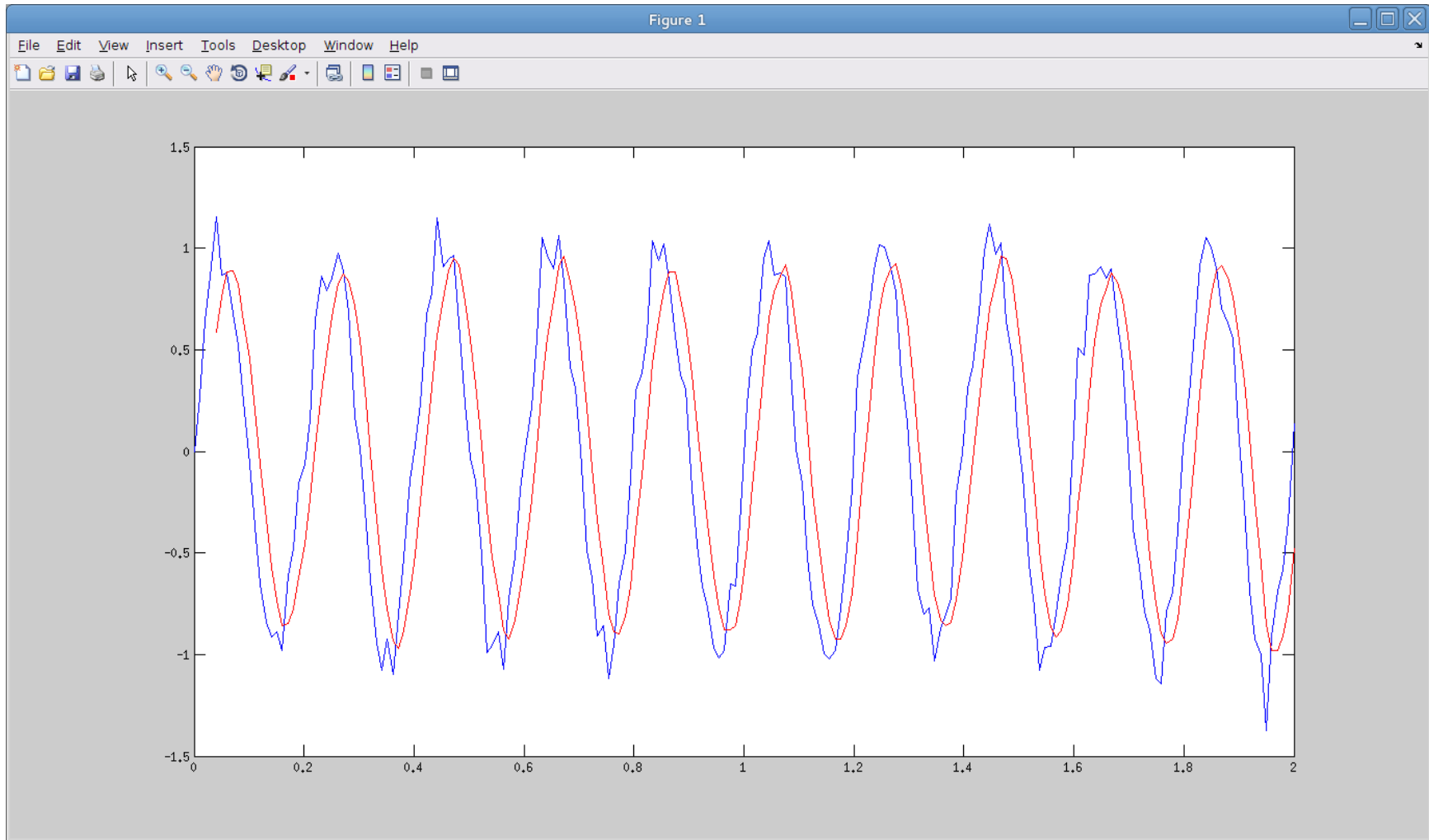


$$y_n = \frac{x_{n-2} + x_{n-1} + x_n}{3}$$

Note that this filter depends only upon present and past values of  $x$  (not upon future values).



# Filtering with trailing box average



- Note output signal has been delayed

# Simple moving average



- Note SMA is delayed

# Takeaway points

- You can filter a signal using a weighted moving average.
- The weights themselves can be considered to be a function
  - This function is the filter kernel
- Different kernels have different properties
- What kernel to use depends upon your specific signal and your specific goals.



# Fourier series and Fourier transforms



Joseph Fourier  
1768 -- 1830

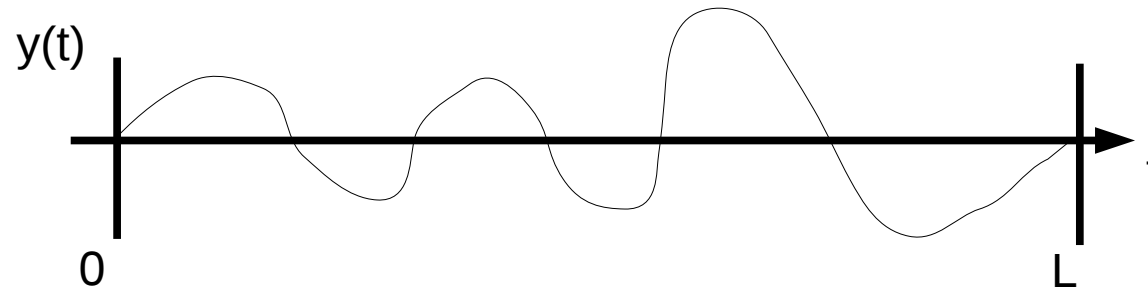
# Goal: Expanding a function

- It's all about writing an expansion for a given function  $y(t)$ .
- Recall Taylor's series expansion around a point:

$$y(t-t_0) = a_0 + a_1(t-t_0) + a_2(t-t_0)^2 + a_3(t-t_0)^3 + \dots$$

- Properties:
  - Provides good approximation to  $y(t-t_0)$  in neighborhood  $t \approx t_0$
  - Usually only need a few terms for good approximation.

# Consider function on finite interval



- Taylor expansion not very good here – polynomial order required is too high.
- Can I do a different expansion which works over entire interval?
- Note this fcn is zero at boundaries
- Yes: Fourier sin series:

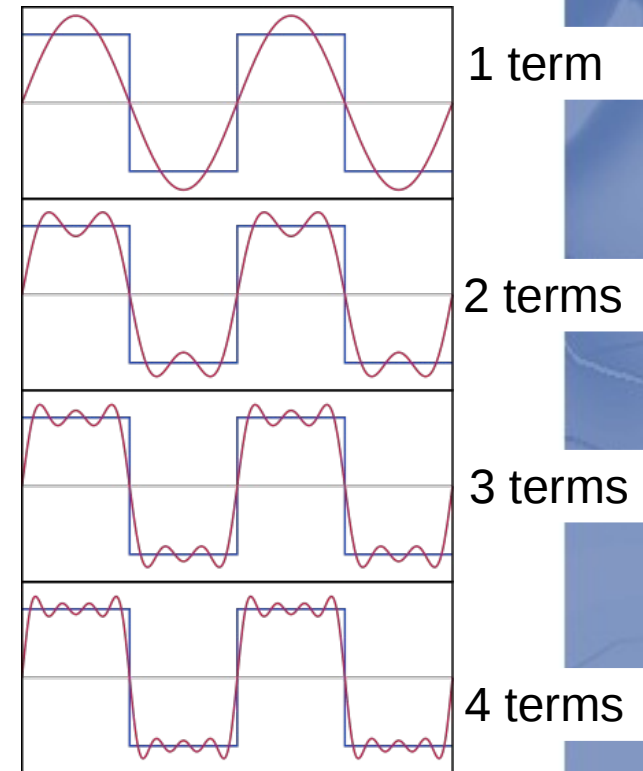
$$y(t) = a_1 \sin\left(\frac{\pi t}{L}\right) + a_2 \sin\left(\frac{2\pi t}{L}\right) + a_3 \sin\left(\frac{3\pi t}{L}\right) + \dots$$

# Fourier sin series

- Important theorem: I can expand any bounded, continuous function which is zero at the boundaries as a sum of sin functions (Fourier, 18<sup>th</sup> Century).

$$y(t) = \sum_{n=1}^{\infty} a_n \sin(n\pi t/L)$$

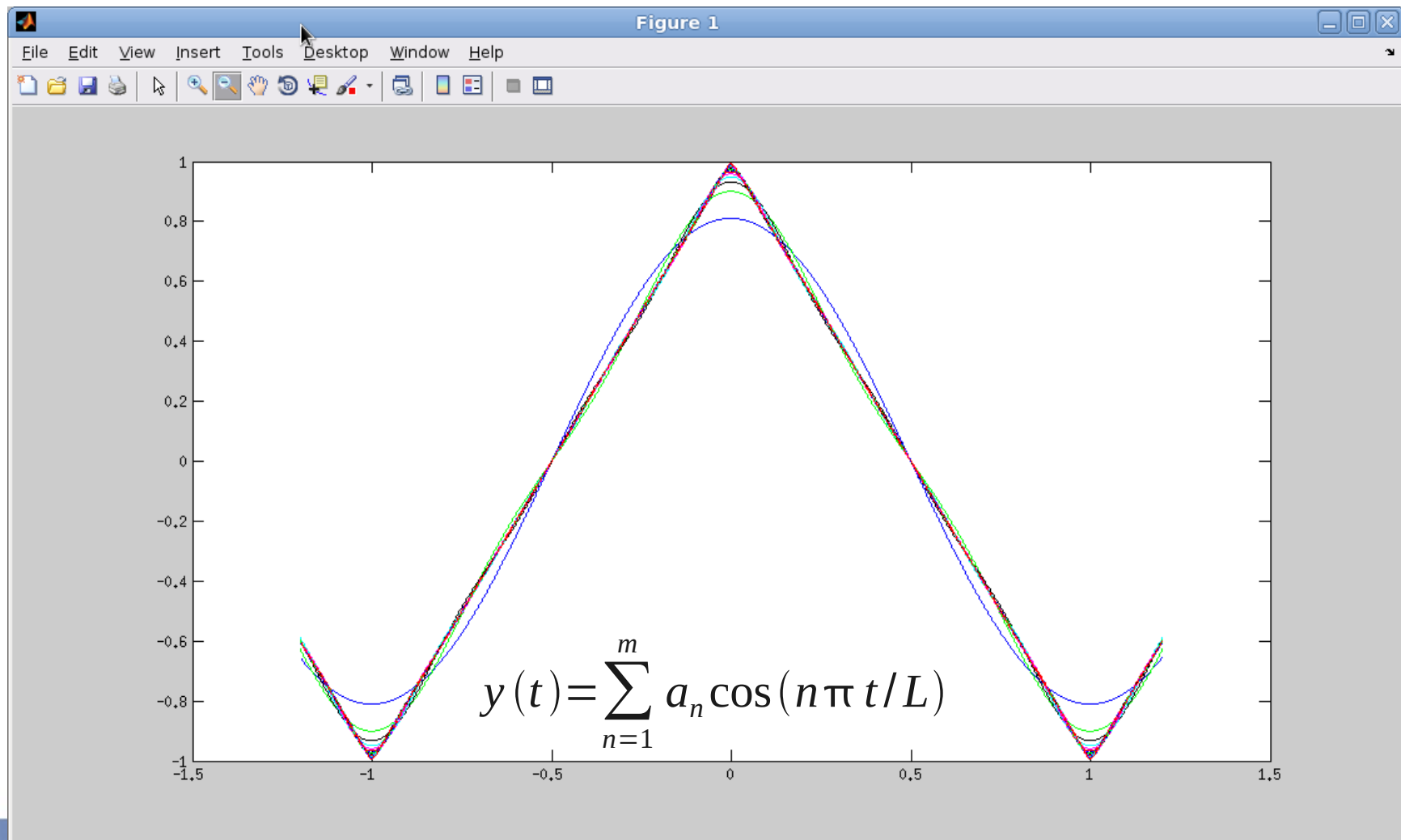
- I might need an infinite number of terms.
- Series converges over entire interval.
- Each term in expansion has coefficient  $a_n$
- But how to get coefficients?



There is a similar theorem involving  $\cos(t)$

# Fourier series is remarkable

- Says you can expand even functions with discontinuities using sin/cos functions.



# How to get coefficients?

- Consider integrating the product of two sin functions:

$$\int_0^L dt \sin\left(\frac{n\pi t}{L}\right) \sin\left(\frac{m\pi t}{L}\right) \quad \swarrow \text{m, n are integers}$$

- Recall trig identity:

$$\sin(x) \sin(y) = \frac{1}{2} (\cos(x-y) - \cos(x+y))$$

- So: 
$$\int_0^L dt \sin\left(\frac{n\pi t}{L}\right) \sin\left(\frac{m\pi t}{L}\right)$$
$$= \frac{1}{2} \int_0^L dt \left[ \cos\left(\frac{(n-m)\pi t}{L}\right) - \cos\left(\frac{(n+m)\pi t}{L}\right) \right]$$



# Deriving coefficients.....

- Consider expression

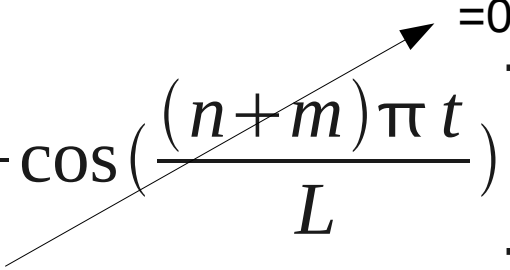
$$\frac{1}{2} \int_0^L dt \left[ \cos\left(\frac{(n-m)\pi t}{L}\right) - \cos\left(\frac{(n+m)\pi t}{L}\right) \right]$$

- When  $n \neq m$  we have two terms like:

$$\begin{aligned} & \int_0^L dt \cos\left(\frac{p\pi t}{L}\right) \quad \leftarrow \begin{array}{l} \text{p is integer} \\ \text{Draw picture on} \\ \text{blackboard to show why} \\ \text{this integrates to zero} \end{array} \\ &= \frac{L}{p\pi} \sin\left(\frac{p\pi t}{L}\right) \Big|_0^L \\ &= \frac{L}{p\pi} (\sin \overset{0}{p\pi} - 0) = 0 \end{aligned}$$



When  $n = m$ ...

$$\begin{aligned} & \frac{1}{2} \int_0^L dt \left[ \cos\left(\frac{(n-m)\pi t}{L}\right) - \cos\left(\frac{(n+m)\pi t}{L}\right) \right] \\ &= \frac{1}{2} \int_0^L dt \cos\left(\frac{0\pi t}{L}\right) \\ &= \frac{L}{2} \end{aligned}$$


- Conclusion: integral is non-zero only when  $n = m$ .

# Orthogonal functions

- Sin functions are orthogonal over interval  $[0, L]$

$$\int_0^L dt \sin\left(\frac{n\pi t}{L}\right) \sin\left(\frac{m\pi t}{L}\right) \begin{cases} = 0 & \text{for } n \neq m \\ = \frac{L}{2} & \text{for } n = m \end{cases}$$

- Similar to orthogonality of vectors:

$$\vec{u} \cdot \vec{v} \begin{cases} = 0 & \text{for } \vec{u} \neq \vec{v} \\ = C & \text{for } \vec{u} = \vec{v} \end{cases}$$

# Consider what this means for Fourier expansion

- Start with

$$y(t) = \sum_{n=1}^{\infty} a_n \sin(n\pi t/L)$$

- Multiply through both sides and integrate:

$$\int_0^L dt y(t) \sin\left(\frac{m\pi t}{L}\right) = \sum_{n=1}^{\infty} a_n \int_0^L dt \sin\left(\frac{m\pi t}{L}\right) \sin\left(\frac{n\pi t}{L}\right)$$

- Use orthogonality:

Method to get coefficients

$$a_m = \frac{2}{L} \int_0^L dt y(t) \sin\left(\frac{m\pi t}{L}\right)$$

# Therefore, we can go in two directions

- Fourier series expansion:

$$y(t) \Leftrightarrow \sum_{n=1}^{\infty} a_n \sin(n\pi t/L)$$

- You can go back and forth:

$$y(t) = \sum_{n=1}^{\infty} a_n \sin(n\pi t/L)$$

Get function from coefficients



$$a_m = \frac{2}{L} \int_0^L dt y(t) \sin\left(\frac{m\pi t}{L}\right)$$

Get coefficients from function


# Generalize to any function defined on an interval

- You can expand any function, regardless of values on boundary using:

Real  $y(t)$

$$y(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n \cos(\omega_n t) + \sum_{n=1}^{\infty} b_n \sin(\omega_n t)$$


a, b are real



Complex  $y(t)$

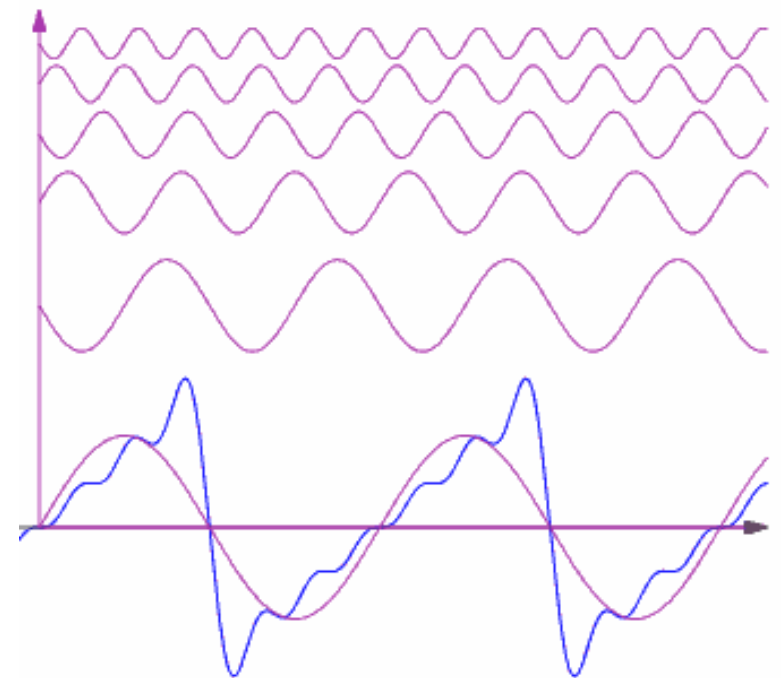
$$y(t) = \sum_{n=-\infty}^{\infty} c_n e^{-i\omega_n t}$$

c is complex



# Consider meaning of $a_n$ coefficients

- Define  $\omega_n = n\pi/L$
- Then Fourier series is  $y(t) = \sum_{n=1}^{\infty} a_n \sin(\omega_n t)$
- Interpret  $\omega_n$  as a frequency
- Height of  $a_n$  determines amplitude of that frequency component in signal  $y(t)$ .
- **Key point:** Any signal can be viewed as composed of a sum of sin/cos waves.



# MIT Mathlets

- Demo:  
<http://mathlets.org/mathlets/fourier-coefficients/>

- To generate square waves, coefficients are:

$$a_n = \frac{4}{n\pi} \quad \text{Odd } n$$

$$= 0 \quad \text{Even } n$$

```
>> n = 1:2:11
```

```
n =
```

```
1 3 5 7 9 11
```

```
>> an = (4./(n*pi))'
```

```
an =
```

```
1.273239544735163  
0.424413181578388  
0.254647908947033  
0.181891363533595  
0.141471060526129  
0.115749049521378
```



# Complex Fourier series

- Fourier series expansion:

$$y(t) = \sum_{n=-\infty}^{\infty} a_n e^{-int}$$

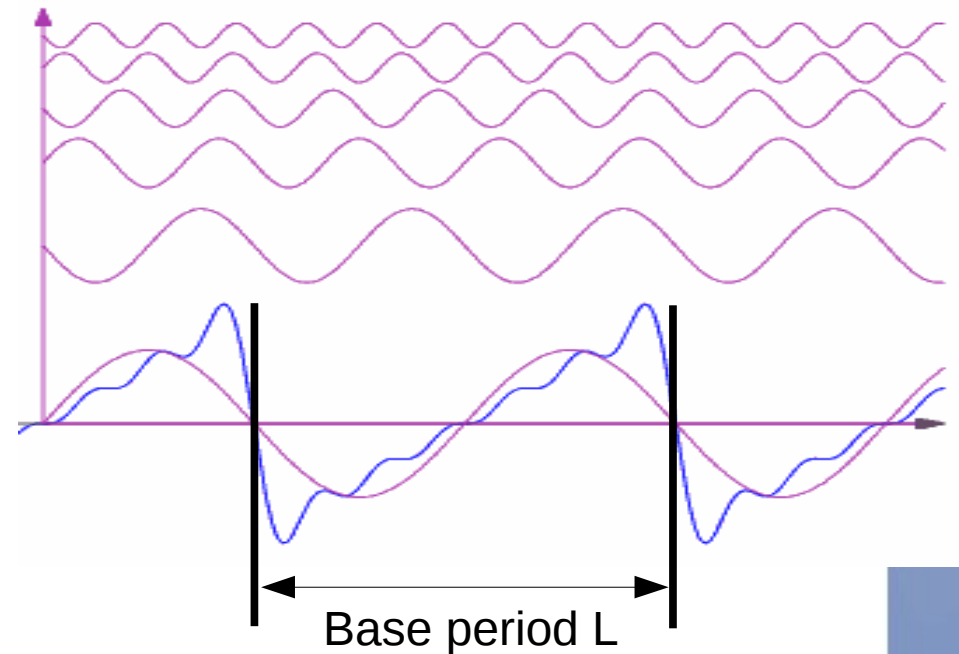
- Given coefficients, compute function:

$$a_m = \frac{1}{2\pi} \int_{-\pi}^{\pi} dt y(t) e^{int}$$

- Note different limits of summation and integration.

# What happens outside interval $[0, L]$ ?

- Basis functions  $\sin$ ,  $\cos$  mean expansion extends to infinity, and is periodic.
- Base period  $L$
- Therefore, you can use Fourier series to expand:
  - Any periodic function
  - Any function defined on a finite interval



# Fourier transform

- Fourier series defined for signal on finite interval or periodic.
- What if signal is infinite (i.e. extends to  $t = \pm\infty$ )?
- Fourier transform pair:

$$Y(\omega) = \int_{-\infty}^{\infty} dt y(t) e^{-i\omega t}$$

Transform to  
frequency domain

$$y(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega Y(\omega) e^{i\omega t}$$

Transform to  
time domain

# Fourier transform vs. series

## Fourier series

$$a_m = \frac{2}{L} \int_0^L dt y(t) \sin\left(\frac{m\pi t}{L}\right)$$

$$y(t) = \sum_{n=1}^{\infty} a_n \sin\left(\frac{n\pi t}{L}\right)$$

- Valid for:
  - Periodic function
  - Function on interval
- Continuous function, discrete spectrum

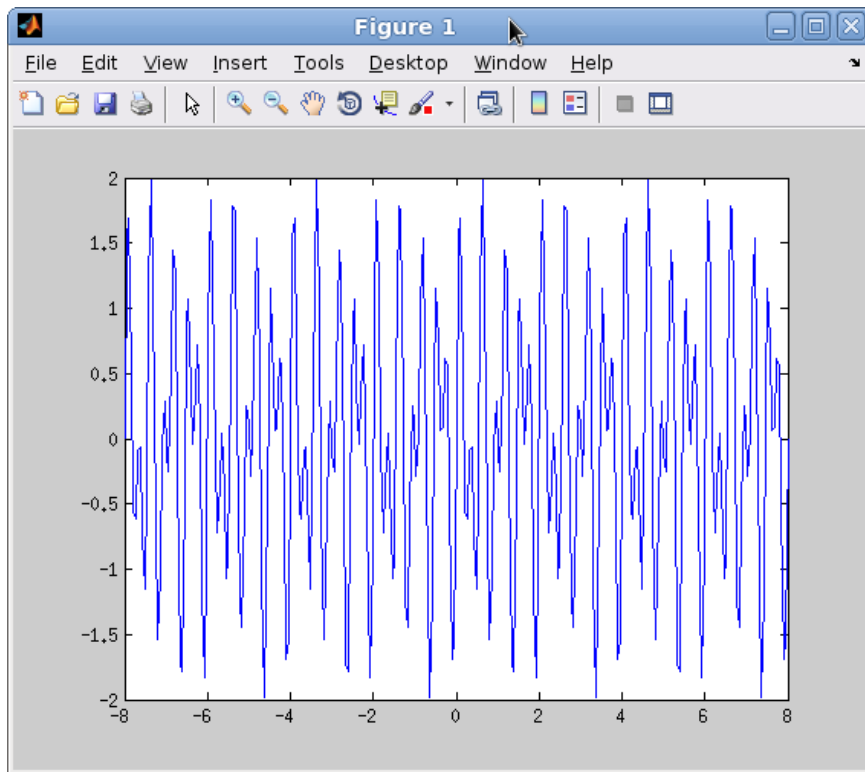
## Fourier transform

$$Y(\omega) = \int_{-\infty}^{\infty} dt y(t) e^{-i\omega t}$$

$$y(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega Y(\omega) e^{i\omega t}$$

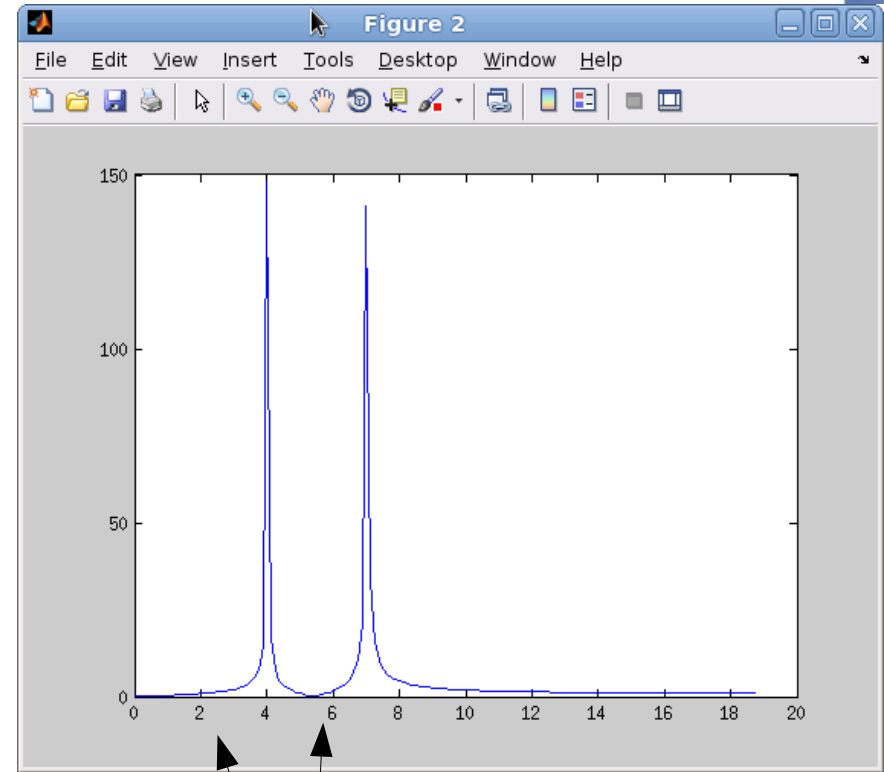
- Valid for any function
- Function and spectrum continuous.

# Fourier transform converts time-varying signal into frequency spectrum



```
f1 = 4;  
f2 = 7;  
w = -t.*t + 64;  
y = w.*(sin(2*pi*f1*t) + sin(2*pi*f2*t));
```

Create signal with two frequencies:  
4Hz and 7Hz.



Take Fourier transform.  
Observe two delta functions  
at 4 and 7 Hz.

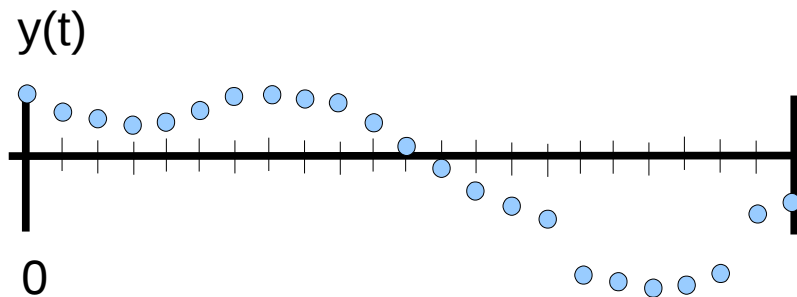
# Time and frequency are duals

- Fourier transform pair: you can go back and forth from time domain to frequency domain.

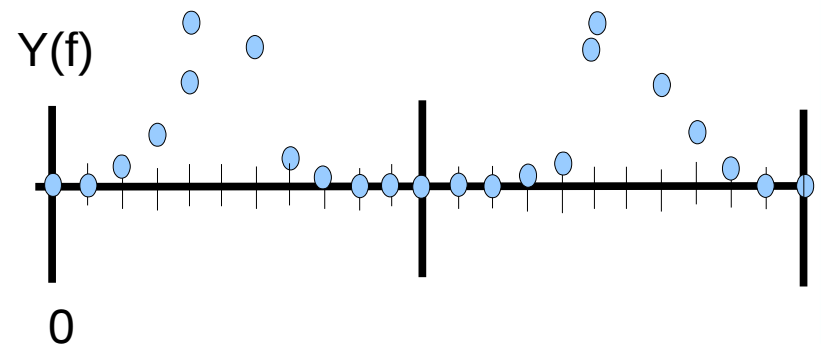
$$y(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega Y(\omega) e^{i\omega t}$$



$$Y(\omega) = \int_{-\infty}^{\infty} dt y(t) e^{-i\omega t}$$

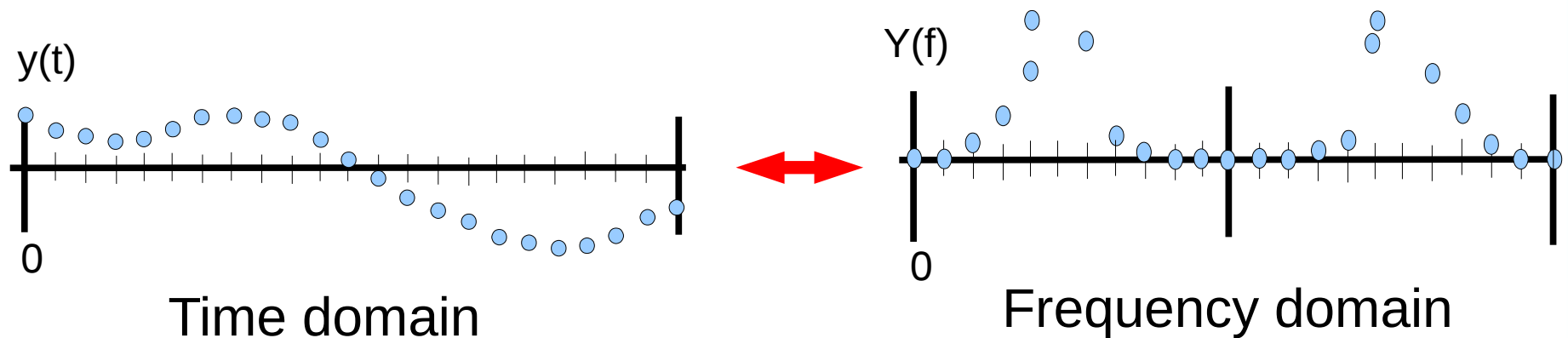


Time domain



Frequency domain

# Time domain and frequency domain

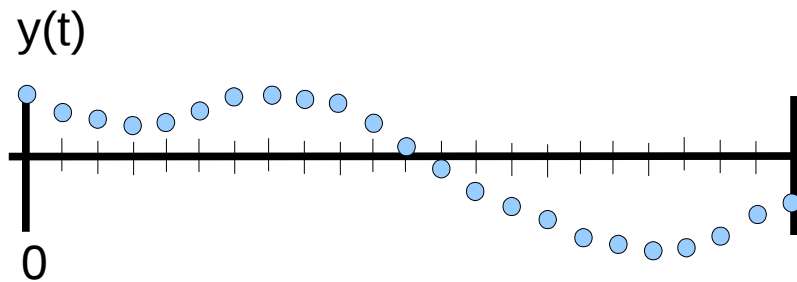




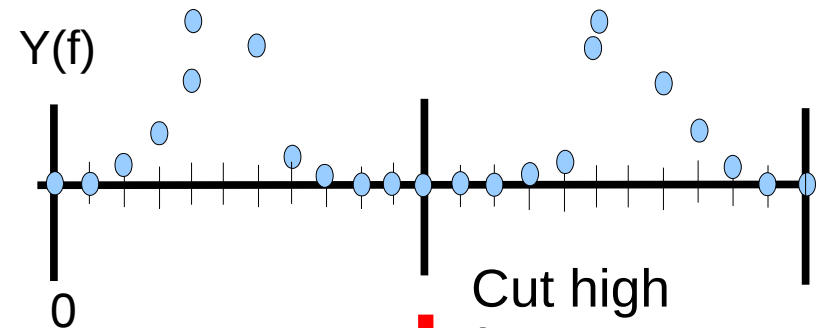
# Application: filtering

Time domain

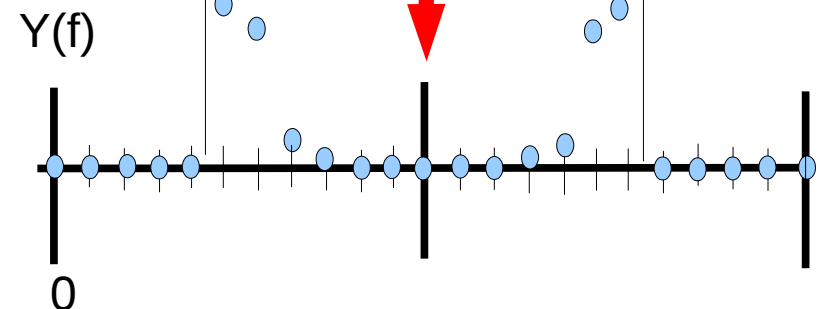
Frequency domain



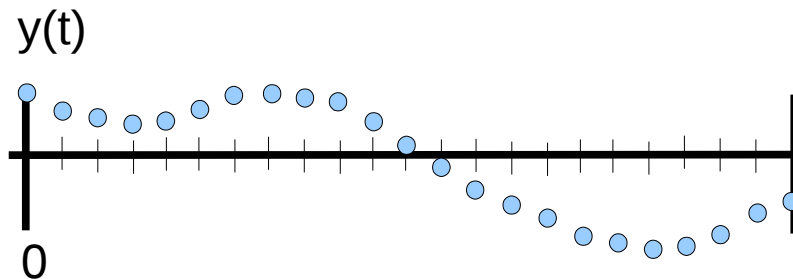
FFT  
→



Cut high  
frequency  
components  
↓



IFFT  
←



Stereo equalizer

# Session summary

- Sampled data
- Simple filters
- Taking numeric derivatives
- Fourier series
- Fourier transform

