

Experimental Methods Lecture 5

September 30th, 2020



Fourier Transforms of Discrete Data

- Two transforms:
 - Discrete-time Fourier Transform (infinite length data series)
 - Discrete Fourier Transform (finite length data series)
- Can they be used to estimate Fourier Transform of original continuous signals?



• The transform

$$s(\phi) = \sum_{k=-\infty}^{\infty} s_k e^{-i k\phi}$$

The inversion formula

$$s_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} s(\phi) e^{ik\phi} d\phi$$

Sequence transform vs continuous transform

$$s_d(\phi) = \frac{1}{T} \sum_{n=-\infty}^{\infty} s_c \left(\frac{\phi}{T} + n \frac{2\pi}{T} \right) = \frac{1}{T} s_c' \left(\frac{\phi}{T} \right)$$

- $s_d(\phi)$: discrete time transform
- $s_c(\omega)$: continuous transform
- $s'_c(\omega)$:continuous transform of the Shannon interpolation of s(t)
- If T fulfils the sampling theorem, then

$$s_d(\phi) = \frac{1}{T} s_c \left(\frac{\phi}{T}\right) = \frac{1}{T} s_c' \left(\frac{\phi}{T}\right)$$



Discrete-time transform

- They share almost literally the properties of continuous transform.
- In particular, the transform of the convolution of two sequences

$$x[n] = \sum_{k=-\infty}^{\infty} z[k]y[n-k]$$

is

$$x [\phi] = z [\phi] y [\phi]$$

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Property	Time domain $x[n]$	Frequency domain $X_{2\pi}(\omega)$	Remarks	Reference	И
Linearity	$a\cdot x[n] + b\cdot y[n]$	$a\cdot X_{2\pi}(\omega) + b\cdot Y_{2\pi}(\omega)$	$\hbox{complex numbers a,b}$	[16]:p.294	
Time reversal / Frequency reversal	x[-n]	$X_{2\pi}(-\omega)$		[16]:p.297	
Time conjugation	$x[n]^*$	$X_{2\pi}(-\omega)^*$		[16]:p.291	
Time reversal & conjugation	$x[-n]^*$	$X_{2\pi}(\omega)^*$		[16]:p.291	
Real part in time	$\mathfrak{R}(x[n])$	$\frac{1}{2}(X_{2\pi}(\omega)+X_{2\pi}^*(-\omega))$		[16]:p.291	
Imaginary part in time	$\Im(x[n])$	$rac{1}{2i}(X_{2\pi}(\omega)-X_{2\pi}^*(-\omega))$		[16]:p.291	
Real part in frequency	$\frac{1}{2}(x[n]+x^*[-n])$	$\mathfrak{R}(X_{2\pi}(\omega))$		[16]:p.291	
Imaginary part in frequency	$\frac{1}{2i}(x[n]-x^*[-n])$	$\mathfrak{I}(X_{2\pi}(\omega))$		[16]:p.291	
Shift in time / Modulation in frequency	x[n-k]	$X_{2\pi}(\omega)\cdot e^{-i\omega k}$	integer k	[16]:p.296	
Shift in frequency / Modulation in time	$x[n] \cdot e^{ian}$	$X_{2\pi}(\omega-a)$	real number a	[16]:p.300	
Decimation	x[nM]	$rac{1}{M}\sum_{m=0}^{M-1}X_{2\pi}\left(rac{\omega-2\pi m}{M} ight)$ [F]	integer M		
Time Expansion	$\left\{ \begin{array}{ll} x[n/M] & n{=}\mathrm{multiple\ of\ M} \\ 0 & \mathrm{otherwise} \end{array} \right.$	$X_{2\pi}(M\omega)$	integer M	[1]:p.172	
Derivative in frequency	$rac{n}{i}x[n]$	$rac{dX_{2\pi}(\omega)}{d\omega}$		[16]:p.303	
Integration in frequency					
Differencing in time	x[n]-x[n-1]	$\left(1-e^{-i\omega} ight)X_{2\pi}(\omega)$			
Summation in time	$\sum_{m=-\infty}^n x[m]$	$rac{1}{(1-e^{-i\omega})}X_{2\pi}(\omega)+\pi X(0)\sum_{k=-\infty}^{\infty}\delta(\omega-2\pi k)$			
Convolution in time / Multiplication in frequency	x[n]*y[n]	$X_{2\pi}(\omega)\cdot Y_{2\pi}(\omega)$		[16]:p.297	
Multiplication in time / Convolution in frequency	$x[n] \cdot y[n]$	$rac{1}{2\pi}\int_{-\pi}^{\pi}X_{2\pi}(u)\cdot Y_{2\pi}(\omega- u)d u$	Periodic convolution	[16]:p.302	
Cross correlation	$\rho_{xy}[n] = x[-n]^* * y[n]$	$R_{xy}(\omega) = X_{2\pi}(\omega)^* \cdot Y_{2\pi}(\omega)$			
Parseval's theorem	$E_{xy} = \sum_{n=-\infty}^{\infty} x[n] \cdot y[n]^*$	$E_{xy} = rac{1}{2\pi} \int_{-\pi}^{\pi} X_{2\pi}(\omega) \cdot Y_{2\pi}(\omega)^* d\omega$		[16]:p.302	



- Assume you have a finite-length data sequence s_n with $0 \le n \le N-1$.
- We can define the following function of the integer k

$$\hat{s}_{k} = \sum_{n=0}^{N-1} s_{n} e^{-i\frac{2\pi}{N}kn}$$

• The function is periodic with period N, thus only the values for $0 \le k \le N-1$ have an independent meaning



 \hat{s}_k is a transform. Indeed define

$$\widetilde{S}_{m} = \frac{1}{N} \sum_{k=0}^{N-1} \hat{S}_{k} e^{i\frac{2\pi}{N}km}$$

Substituting \hat{s}_k from its definition

$$\widetilde{s}_{m} = \frac{1}{N} \sum_{k=0}^{N-1} \left(\sum_{n=0}^{N-1} s_{n} e^{-i\frac{2\pi}{N}k n} \right) e^{i\frac{2\pi}{N}k m} = \sum_{n=0}^{N-1} s_{n} \left(\frac{1}{N} \sum_{k=0}^{N-1} e^{i\frac{2\pi}{N}k(m-n)} \right)$$

A well known rule

$$\sum_{k=0}^{N-1} e^{ika} = \frac{1 - e^{iNa}}{1 - e^{ia}}$$

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(1)

(2)

Consider the sum of the first n terms of the geometric series

$$s_n = a + ax + ax^2 + ax^3 + \ldots + ax^{n-1}$$

Multiply both sides by x

$$xs_n = ax + ax^2 + ax^3 + ax^4 + \ldots + ax^n$$

Subtract Equation (2) from Equation (1)

$$(1-x)s_n = a - ax^n$$
$$= a(1-x^n)$$

If $x \neq 1$ divide both sides by 1 - x to get

$$s_n = \frac{a(1-x^n)}{1-x} \qquad (x \neq 1) \tag{3}$$

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• \hat{s}_k is a transform. Indeed define

$$\widetilde{s}_{m} = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}_{k} e^{i\frac{2\pi}{N}km}$$

• Substituting \hat{s}_k from its definition

$$\widetilde{s}_{m} = \frac{1}{N} \sum_{k=0}^{N-1} \left(\sum_{n=0}^{N-1} s_{n} e^{-i\frac{2\pi}{N}kn} \right) e^{i\frac{2\pi}{N}km} = \sum_{n=0}^{N-1} s_{n} \left(\frac{1}{N} \sum_{k=0}^{N-1} e^{i\frac{2\pi}{N}k(m-n)} \right)$$

A well known rule

$$\sum_{k=0}^{N-1} e^{ika} = \frac{1 - e^{iNa}}{1 - e^{ia}}$$

• Then
$$\widetilde{s}_{m} = \frac{1}{N} \sum_{n=0}^{N-1} s_{n} \frac{1 - e^{iN\frac{2\pi}{N}(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} = \frac{1}{N} \sum_{n=0}^{N-1} s_{n} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}}$$



• A special formula

$$\frac{1}{N} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}}$$

• If $m \neq n$ and m, n < N

$$\frac{1}{N} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} = 0$$

• Limit for $m \rightarrow n$

$$m \to n : \frac{1}{N} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} \approx \frac{1}{N} \frac{2\pi(m-n)}{\frac{2\pi}{N}(m-n)} \to 1$$

$$\frac{1}{N} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} = \delta_{m,n}$$

$$1 - e^{i\frac{2\pi}{N}(m-n)}$$

• Then

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Back to the calculation

$$\widetilde{S}_{m} = \frac{1}{N} \sum_{n=0}^{N-1} S_{n} \frac{1 - e^{iN\frac{2\pi}{N}(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} = \frac{1}{N} \sum_{n=0}^{N-1} S_{n} \frac{1 - e^{i2\pi(m-n)}}{1 - e^{i\frac{2\pi}{N}(m-n)}} = \sum_{n=0}^{N-1} \delta_{n,m} S_{n} = S_{m}$$

In summary

$$\hat{s}_{k} = \sum_{n=0}^{N-1} s_{n} e^{-i\frac{2\pi}{N}kn}$$
 $s_{n} = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}_{k} e^{i\frac{2\pi}{N}kn}$



Discrete Fourier Transform of Sampled Signals

Take a signal of duration

$$\Delta T = (N-1) T \approx NT$$

• Sampled with sampling time T. The discrete-time Fourier transform of the signal padded with 0's is

$$s[\phi] = \sum_{n=1}^{\infty} s_n e^{-i\phi n}$$

Compare with

$$\hat{\mathbf{s}}_{k} = \sum_{n=0}^{N-1} \mathbf{s}_{n} e^{-i\frac{2\pi}{N}kn}$$

• It follows that the \hat{s}_k are samples of $s[\phi]$

$$\hat{s}_k = s \left[\phi = (k 2\pi/N) \right]$$

If the signal has been correctly sampled and truncated

$$\hat{s}_{k} = s_{d} \left[\phi = k \frac{2\pi}{N} \right] = \frac{1}{T} s_{c} \left[\omega = k \frac{2\pi}{NT} \right]$$



Discrete Fourier Transform of Sampled Signals

In conclusion

$$\hat{\mathbf{s}}_{\mathbf{k}} = \frac{1}{T} \mathbf{s}_{\mathbf{c}} \left[\boldsymbol{\omega} = \mathbf{k} \frac{2\pi}{NT} \right]$$

• Thus for a signal that has been correctly sampled and truncated the \hat{s}_k , from which the signal can be reconstructed, are proportional to the samples of the Fourier Transform of the original continuous signal at multiple integers of the fundamental frequency:

$$f_o = \frac{1}{NT} = \frac{1}{\Lambda T}$$

- The resolution of the "spectrum" is 1/(signal duration)!
- This is also the minimum, non-zero frequency for which the "spectrum" is available



$$\hat{s}_{k} = \sum_{n=0}^{N-1} s_{n} e^{-i\frac{2\pi}{N}kn}$$

- Some properties
 - A key property

$$\hat{s}_{N-k} = \sum_{n=0}^{N-1} s_n e^{-i\frac{2\pi}{N}(N-k)n} = \sum_{n=0}^{N-1} s_n e^{-i\frac{2\pi}{N}Nn} e^{+i\frac{2\pi}{N}kn} = \sum_{n=0}^{N-1} s_n e^{+i\frac{2\pi}{N}kn} = \hat{s}_k^*$$

- Thus, of the N coefficients only $\approx N/2$ have an independent value

$$\hat{s}_0$$
; $\hat{s}_1 = \hat{s}_{N-1}^*$; $\hat{s}_2 = \hat{s}_{N-2}^*$

Odd N
$$\rightarrow \hat{s}_{(N-1)/2} = \hat{s}_{(N+1)/2}^*$$

Even N $\rightarrow \hat{s}_{N/2-1} = \hat{s}_{N/2+1}^*; \hat{s}_{N/2}$

Even
$$N \to \hat{s}_{N/2-1} = \hat{s}_{N/2+1}^*; \hat{s}_{N/2}$$

 It's a consequence of conservation of information. N real data are transformed into N/2 complex data.

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It's a remnant of the symmetry of the continuous transform

$$s_{N-k} = \sum_{n=0}^{N-1} s_n e^{-i(N-k)\frac{2\pi}{N}n}$$

• Use periodicity:

$$s_{N-k} = \sum_{n=0}^{N-1} s_n e^{-i(N-k-N)\frac{2\pi}{N}n} = s_{-k}$$

Then

$$s_{-k} = s_k^*$$



Independent coefficients

An explicit table

```
1 s[0]
2 s[0] s[1]
3 s[0] Re[s[1]] Im[s[1]]
4 s[0] Re[s[1]] Im[s[1]] s[2]
5 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]]
6 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]] s[3]
7 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]] Re[s[3]] Im[s[3]]
8 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]] Re[s[3]] Im[s[3]] s[4]
9 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]] Re[s[3]] Im[s[3]] Re[s[4]] Im[s[4]]
10 s[0] Re[s[1]] Im[s[1]] Re[s[2]] Im[s[2]] Re[s[3]] Im[s[3]] Re[s[4]] Im[s[4]] s[5]
```

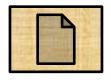
Maximum frequency: Integer Part(N/2)

$$\frac{IntegerPart[N/2]}{NT} \simeq \frac{1}{2T} = f_{Nyquist}$$

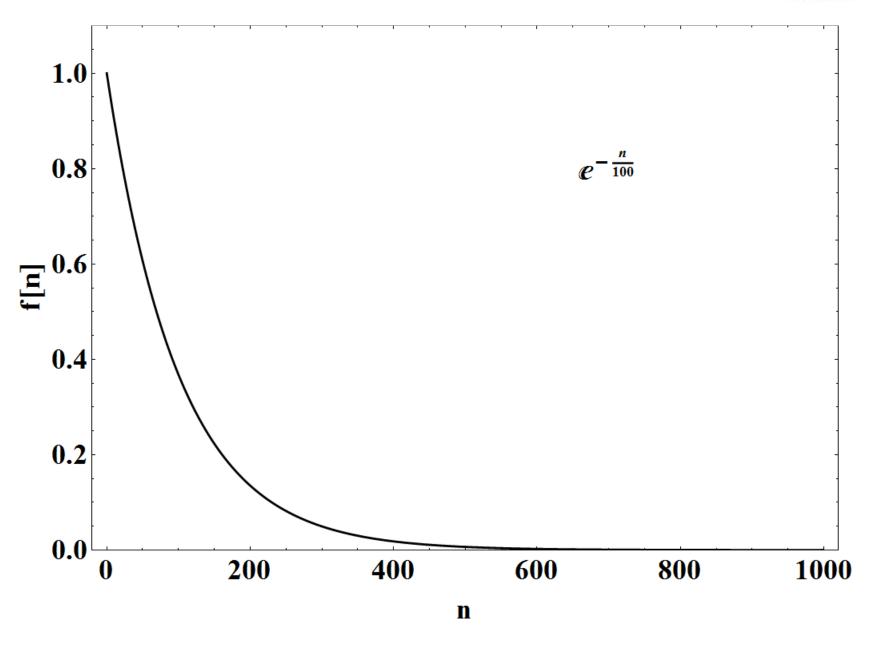


Numerical Examples

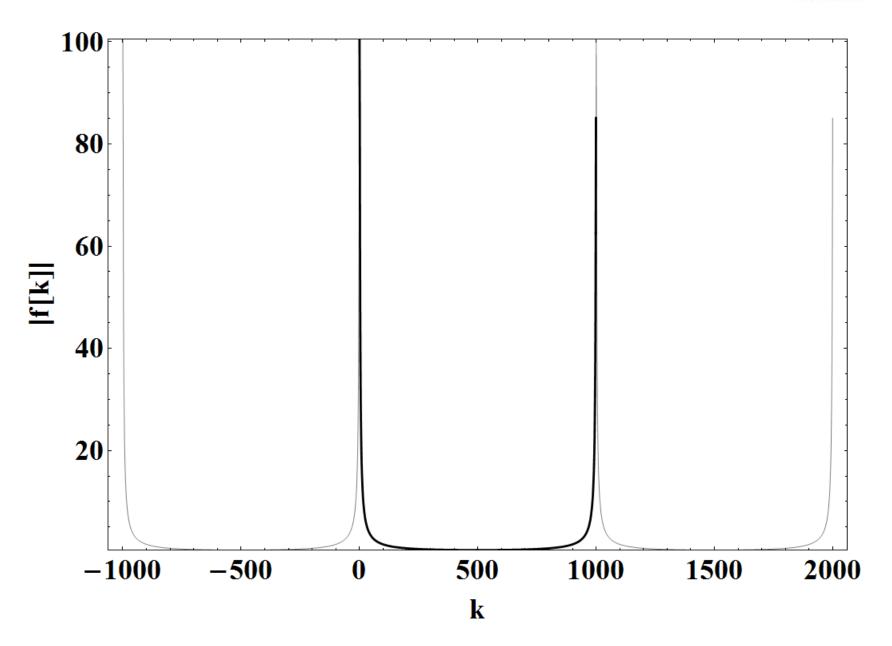
- Discrete Fourier Transforms can be calculated via a very memory-speed-efficient algorithm called the Fast Fourier Transform
- The algorithm is available in any computational environment: MatLabTM, MathematicaTM, C++



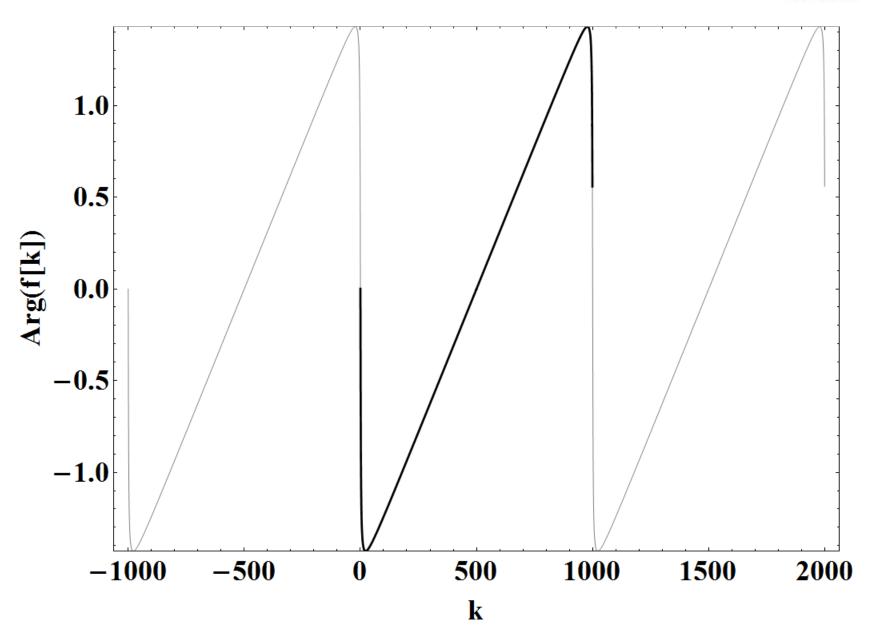


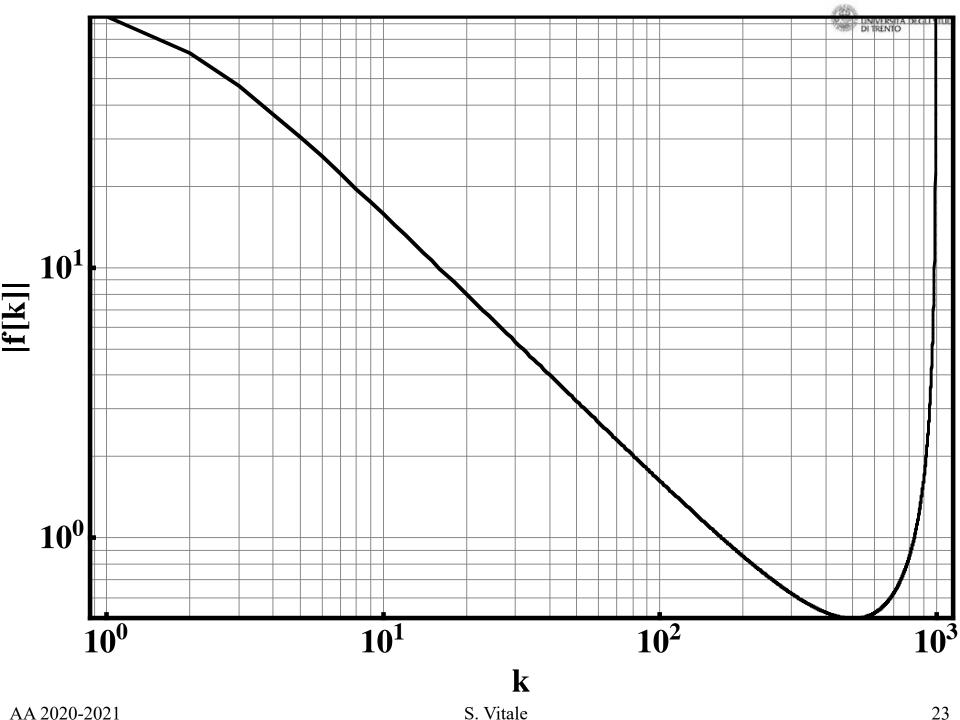




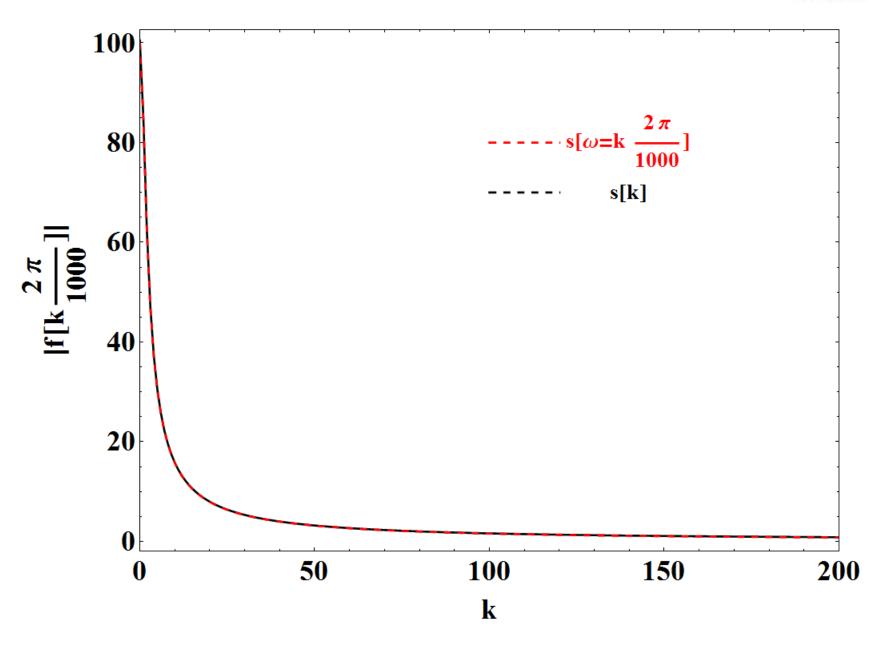




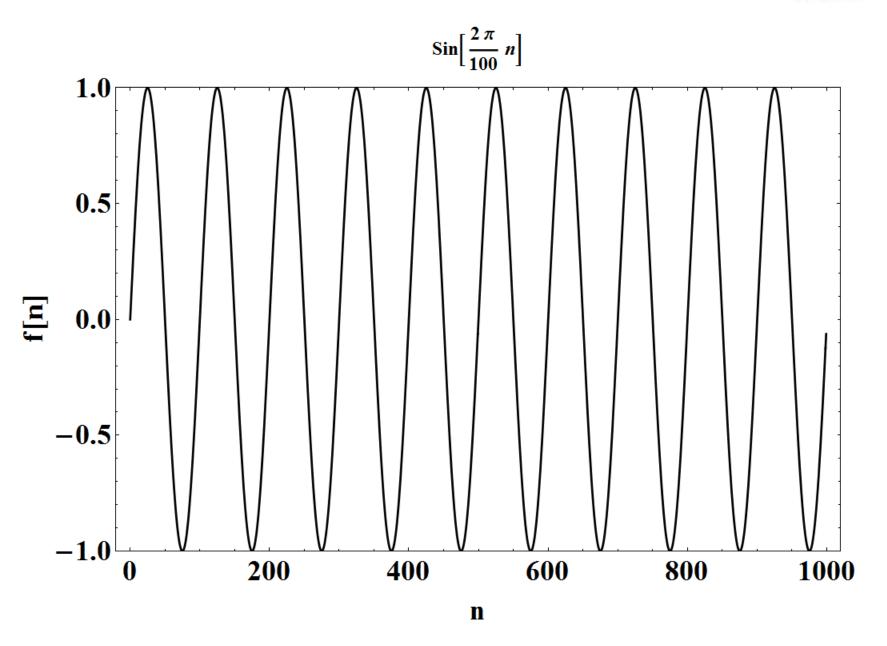




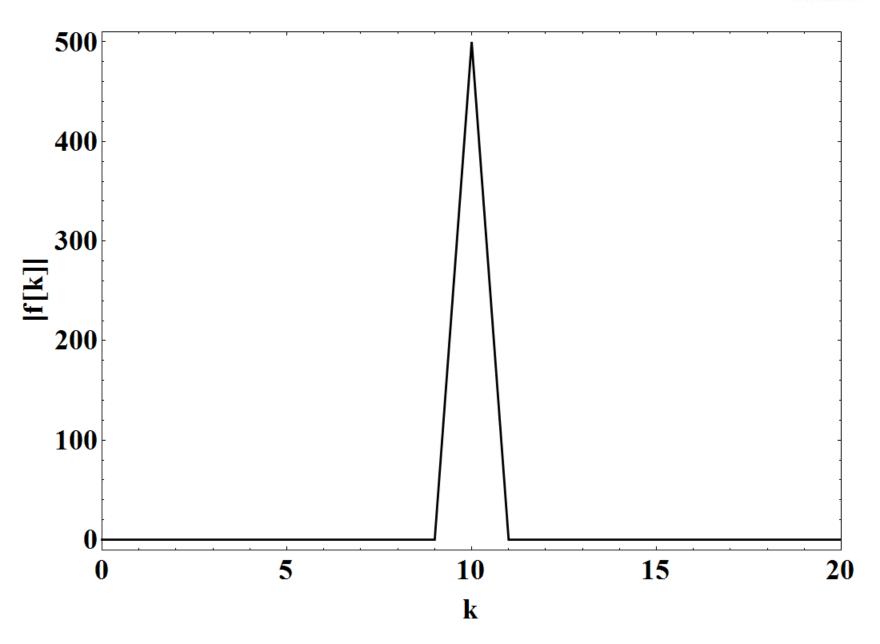




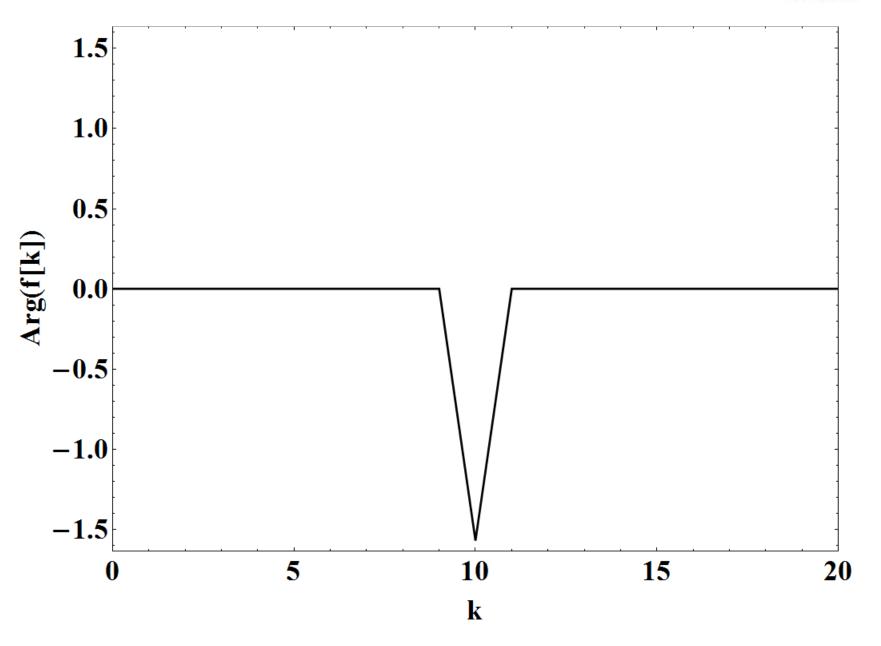














FFT: a very fast algorithm

