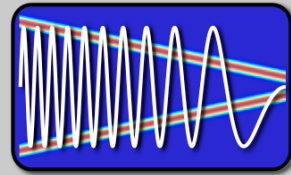


EE123



Digital Signal Processing

Lecture 9

based on slides by J.M. Kahn

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Announcements

- Lab 01 part I and II posted will post III today or tomorrow
- Lab-bash Tuesday 2-3pm 521 Cory
- Three shorter Midterms:
 - 02/26 in class
 - 04/02 in class
 - 04/30 (or 28 TBD) in class
 - 05/05 or 05/06 (TBD) project presentations.
 - Posters and demos

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Announcements

- Last time:
 - Frequency analysis with DFT
 - Windowing
- Today:
 - Continue
 - Effect of zero-padding
 - Start Short-time Fourier Transform

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Windows Properties

These are characteristic of the window type

Window	Main-lobe	Sidelobe δ_s	Sidelobe $-20 \log_{10} \delta_s$
Rect	$\frac{4\pi}{M+1}$	0.09	21
Bartlett	$\frac{8\pi}{M+1}$	0.05	26
Hann	$\frac{8\pi}{M+1}$	0.0063	44
Hamming	$\frac{12\pi}{M+1}$	0.0022	53
Blackman	$\frac{12\pi}{M+1}$	0.0002	74

Most of these (Bartlett, Hann, Hamming) have a transition width that is twice that of the rect window.

Warning: Always check what's the definition of M

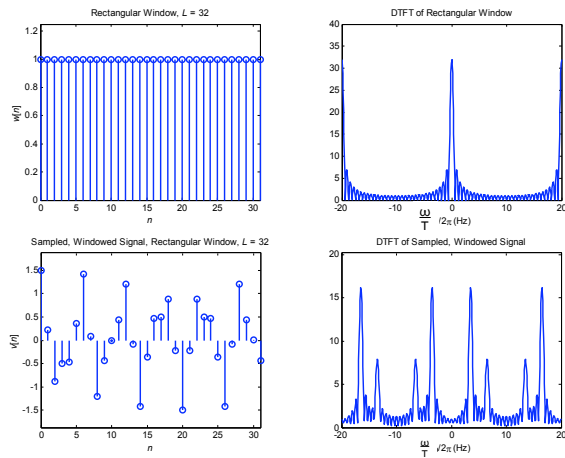
Adapted from *A Course In Digital Signal Processing* by Boaz Porat, Wiley, 1997

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Windows Examples

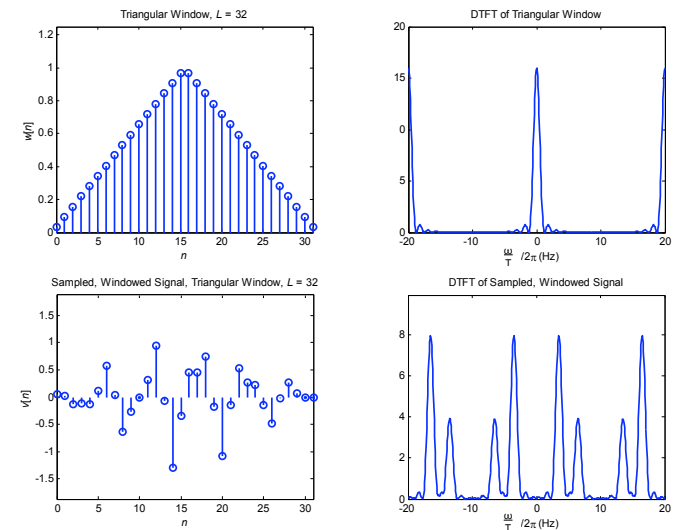
Here we consider several examples. As before, the sampling rate is $\Omega_s/2\pi = 1/T = 20$ Hz.

Rectangular Window, $L = 32$



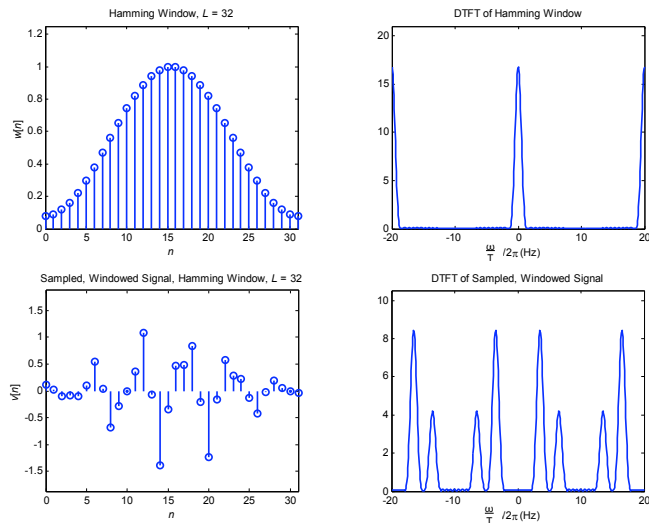
Windows Examples

Triangular Window, $L = 32$



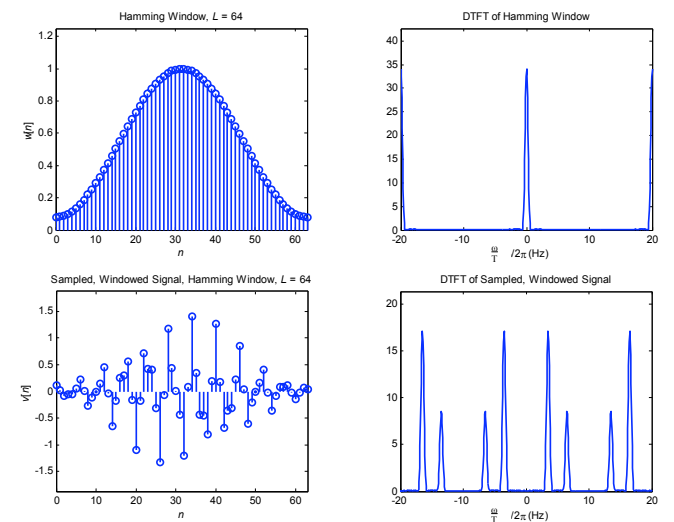
Windows Examples

Hamming Window, $L = 32$



Windows Examples

Hamming Window, $L = 64$



Optimal Window: Kaiser

- Minimum main-lobe width for a given side-lobe energy %

$$\frac{\int_{\text{sidelobes}} |H(e^{j\omega})|^2 d\omega}{\int_{-\pi}^{\pi} |H(e^{j\omega})|^2 d\omega}$$

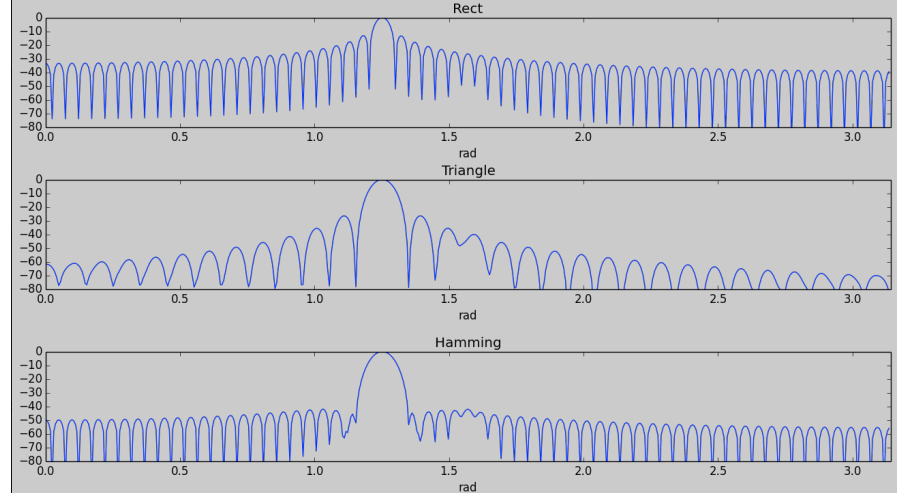
- Window is parametrized with L and β OS Eq 10.12
 - β determines side-lobe level
 - L determines main-lobe width

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Example

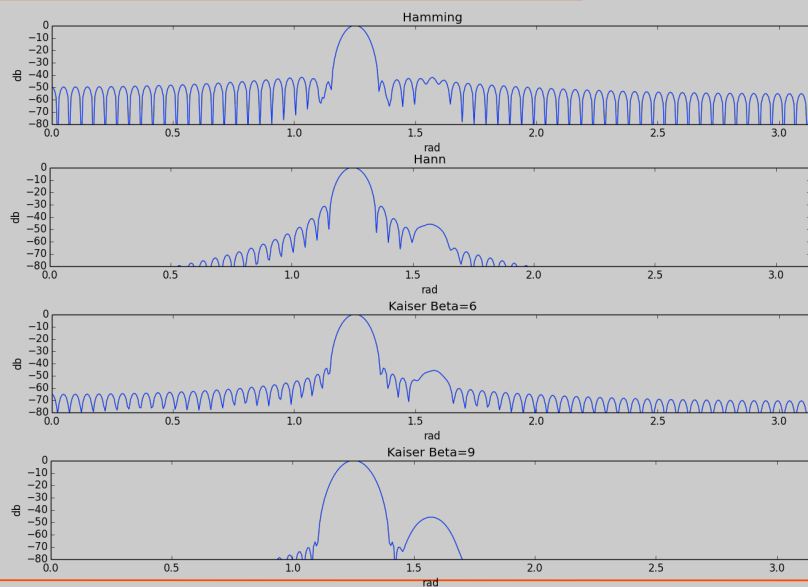
$$y = \sin(2\pi 0.1992n) + 0.005 \sin(2\pi 0.25n) \quad | \quad 0 \leq n < 128$$



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Example



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Zero-Padding

- In preparation for taking an N -point DFT, we may zero-pad the windowed block of signal samples to a block length $N \geq L$:

$$\begin{cases} v[n] & 0 \leq n \leq L-1 \\ 0 & L \leq n \leq N-1 \end{cases}$$

- This zero-padding has no effect on the DTFT of $v[n]$, since the DTFT is computed by summing over $-\infty < n < \infty$.

Effect of Zero Padding

- We take the N -point DFT of the zero-padded $v[n]$, to obtain the block of N spectral samples:

$$V[k], \quad 0 \leq k \leq N-1$$

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Zero-Padding

- Consider the DTFT of the zero-padded $v[n]$. Since the zero-padded $v[n]$ is of length N , its DTFT can be written:

$$V(e^{j\omega}) = \sum_{n=0}^{N-1} v[n]e^{-j\omega n}, \quad -\infty < \omega < \infty$$

The N -point DFT of $v[n]$ is given by:

$$V[k] = \sum_{n=0}^{N-1} v[n]W_N^{kn} = \sum_{n=0}^{N-1} v[n]e^{-j(2\pi/N)nk}, \quad 0 \leq k \leq N-1$$

We see that $V[k]$ corresponds to the samples of $V(e^{j\omega})$:

$$V[k] = V(e^{j\omega}) \Big|_{\omega=k\frac{2\pi}{N}}, \quad 0 \leq k \leq N-1$$

To obtain samples at more closely spaced frequencies, we zero-pad $v[n]$ to longer block length N . The spectrum is the same, we just have more samples.

Frequency Analysis with DFT

- Note that the ordering of the DFT samples is unusual.

$$V[k] = \sum_{n=0}^{N-1} v[n]W_N^{nk}$$

The DC sample of the DFT is $k = 0$

$$V[0] = \sum_{n=0}^{N-1} v[n]W_N^{0n} = \sum_{n=0}^{N-1} v[n]$$

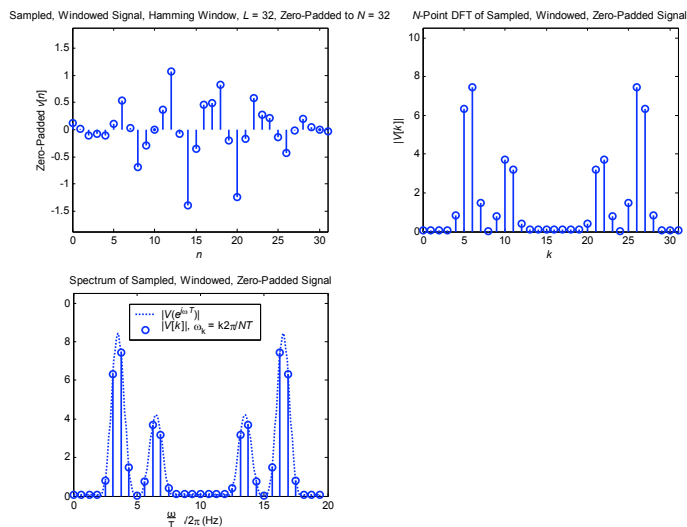
- The positive frequencies are the first $N/2$ samples
- The first $N/2$ negative frequencies are circularly shifted

$$((-k))_N = N - k$$

so they are the last $N/2$ samples. (Use `fftshift` to reorder)

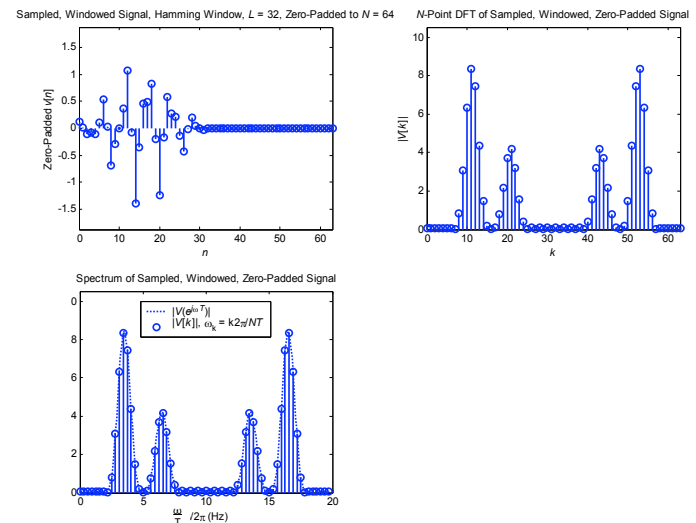
Frequency Analysis with DFT Examples:

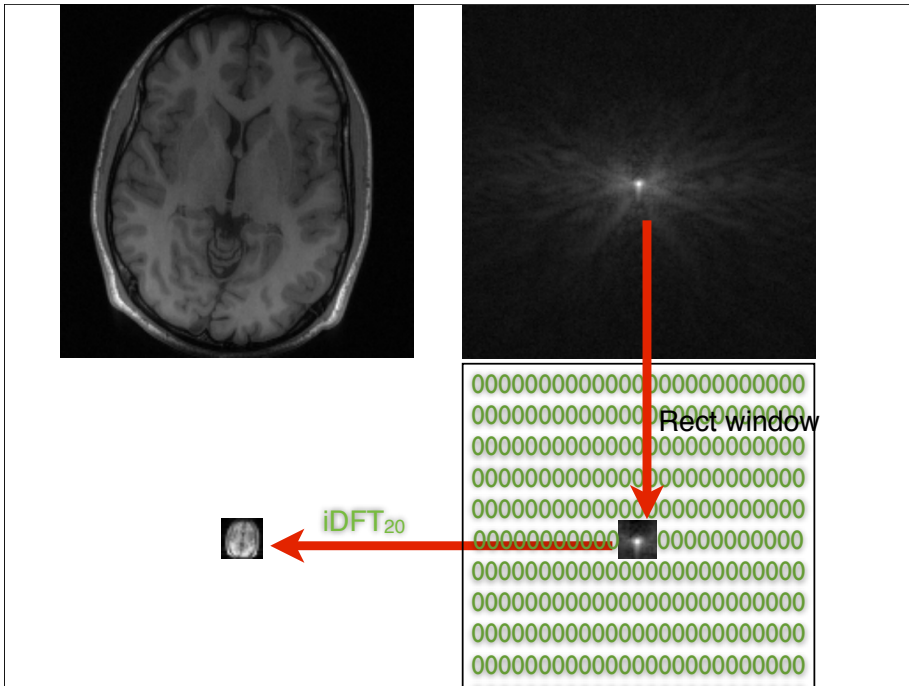
Hamming Window, $L = 32$, $N = 32$



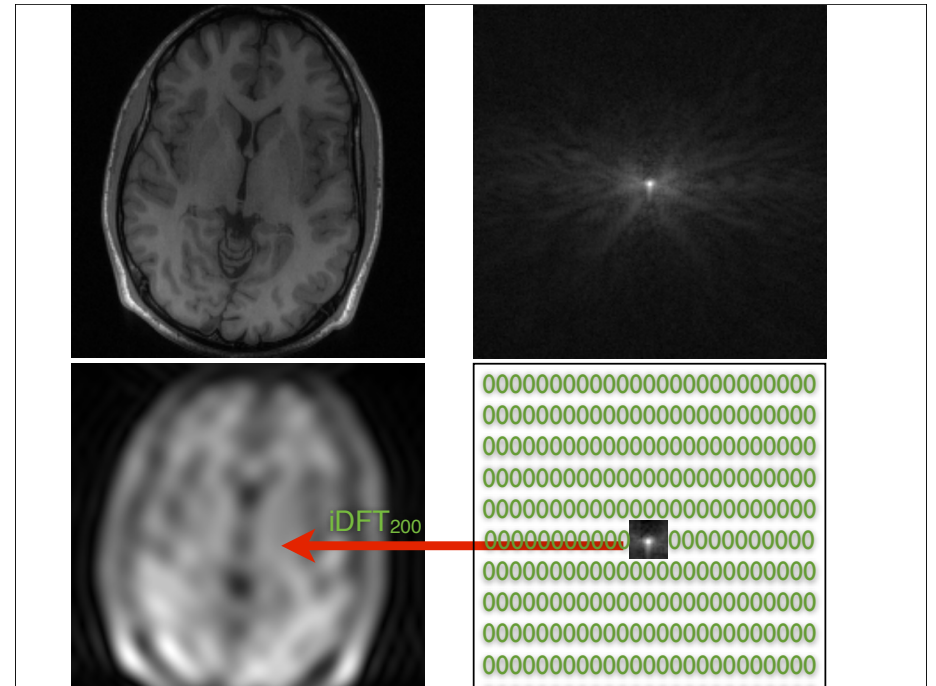
Frequency Analysis with DFT Examples:

Hamming Window, $L = 32$, Zero-Padded to $N = 64$





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0.0T GEMS EMI SPINSE OF NEUR NCES SOLAPUR
 Ex: 2187 Patil Nirmalabai
 Sag T2 045Y F 21870
 Sag L7.1 Acc.
 In: 303 2012 May 11
 Sag L7.1 12:58:19
 512 x 512
 Mag: 1.6x
 A P
 ET: 27
 TR: 2440.0
 TE: 87.8
 8C TL TOP
 3.0mm/1.0sp
 W:591 L:307 21.5 x 21.5cm

A 40 yo pt with a history of lower limb weakness referred for mri screening of brain and whole spine for cord. MRI sagittal T2 screening of dorsal region shows a faint uniform linear high signal at the center of the cord. The signal abnormality likely to represent:

(1) Cord demyelination.
 (2) Syrinx (spinal cord disease).
 (3) Artifact.

Answer : Its an artifact, known as truncation or Gibbs artifact

<http://www.neuroradiologycases.com>

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Frequency Analysis with DFT

- Length of window determines spectral resolution
- Type of window determines side-lobe amplitude.
 (Some windows have better tradeoff between resolution-sidelobe)
- Zero-padding approximates the DTFT better. Does not introduce new information!

Miki Lustig UCB. Based on Course Notes by J.M Kahn Spring 2014, EE123 Digital Signal Processing

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Potential Problems and Solutions

Potential Problems and Solutions

Problem	Possible Solutions
1. Spectral error from aliasing Ch.4	a. Filter signal to reduce frequency content above $\Omega_s/2 = \pi/T$. b. Increase sampling frequency $\Omega_s = 2\pi/T$.
2. Insufficient frequency resolution.	a. Increase L b. Use window having narrow main lobe.
3. Spectral error from leakage	a. Use window having low side lobes. b. Increase L
4. Missing features due to spectral sampling.	a. Increase L , b. Increase N by zero-padding $v[n]$ to length $N > L$.

iSpectrum Example

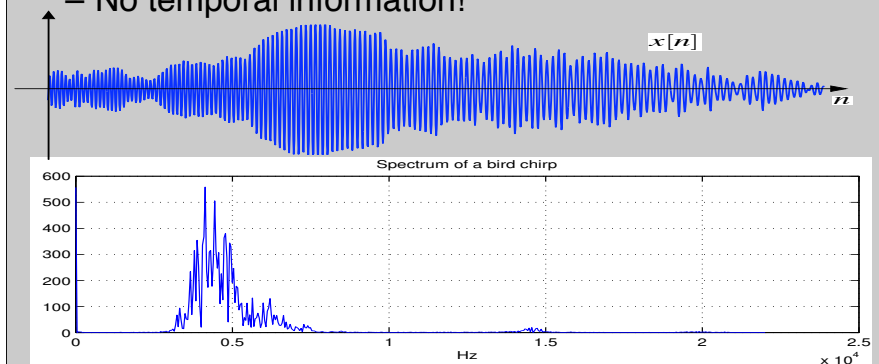
Discrete Transforms (Finite)

- DFT is only one out of a LARGE class of transforms
- Used for:
 - Analysis
 - Compression
 - Denoising
 - Detection
 - Recognition
 - Approximation (Sparse)

Sparse representation has been one of the hottest research topics in the last 15 years in sp

Example of spectral analysis

- Spectrum of a bird chirping
 - Interesting,.... but...
 - Does not tell the whole story
 - No temporal information!



Time Dependent Fourier Transform

- To get temporal information, use part of the signal around every time point

$$X[n, \omega] = \sum_{m=-\infty}^{\infty} x[n+m]w[m]e^{-j\omega m}$$

*Also called Short-time Fourier Transform (STFT)

- Mapping from 1D \Rightarrow 2D, n discrete, ω cont.
- Simply slide a window and compute DTFT

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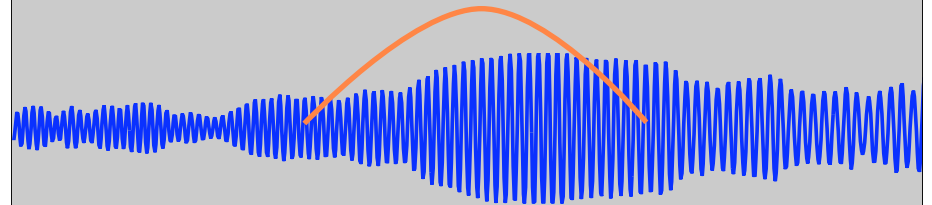
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Time Dependent Fourier Transform

- To get temporal information, use part of the signal around every time point

$$X[n, \omega] = \sum_{m=-\infty}^{\infty} x[n+m]w[m]e^{-j\omega m}$$

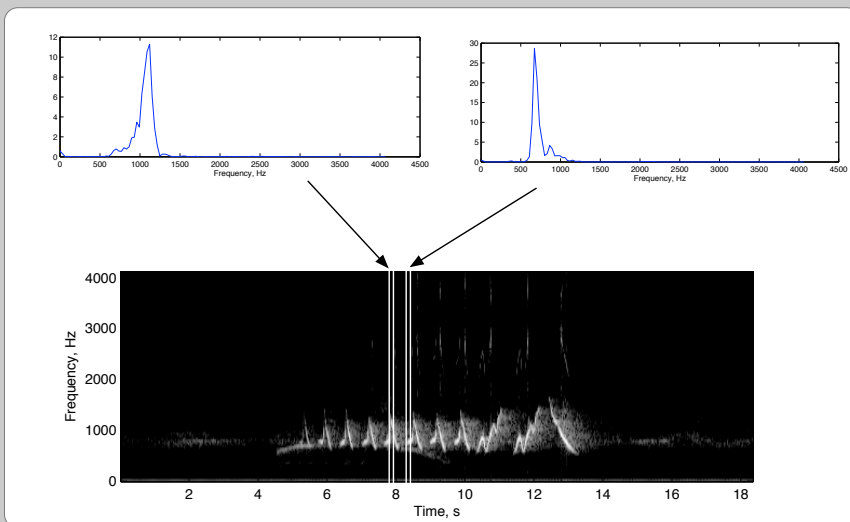
*Also called Short-time Fourier Transform (STFT)



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Spectrogram



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Discrete Time Dependent FT

$$X_r[k] = \sum_{m=0}^{L-1} x[rR+m]w[m]e^{-j2\pi km/N}$$

- L - Window length
- R - Jump of samples
- N - DFT length
- Tradeoff between time and frequency resolution

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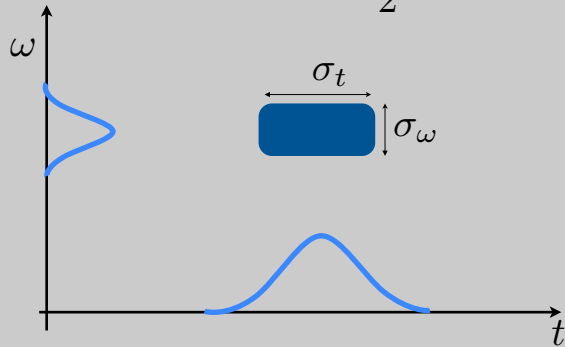
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Heisenberg Boxes



• Time-Frequency uncertainty principle

$$\sigma_t \cdot \sigma_\omega \geq \frac{1}{2}$$



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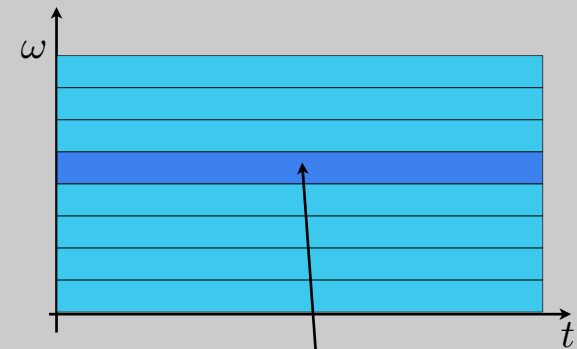
DFT

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N}$$

$$\Delta\omega = \frac{2\pi}{N}$$

$$\Delta t = N$$

$$\Delta\omega \cdot \Delta t = 2\pi$$



one DFT coefficient

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