


# Discrete Fourier Transform

Digital Signal Processing with a focus on audio signals

Instructor: *Fabio Antonacci*

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# Review: road map to Fourier Kingdom

	<i>APERIODIC in time CONTINUOUS in frequency</i>	<i>PERIODIC in time DISCRETE in frequency</i>
<i>CONTINUOUS in time APERIODIC in frequency</i>	<p>Fourier Transform</p> $X(j\Omega) = \int_{-\infty}^{\infty} x(t)e^{-j\Omega t} dt$ $x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(j\Omega)e^{j\Omega t} d\Omega$	<p>Fourier Series</p> $a_k = \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)e^{-j\frac{2\pi kt}{T}} dt$ $x(t) = \sum_{k=-\infty}^{\infty} a_k e^{j\frac{2\pi kt}{T}}$
<i>DISCRETE in time PERIODIC in frequency</i>	<p>Discrete-Time Fourier Transform (DTFT)</p> $X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x(n)e^{-j\omega n}$ $x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega})e^{j\omega n} d\omega$	

# Motivations behind the DFT

- ▶ In the previous lesson we introduced the DTFT, which operates on discrete signals of indefinite length
- ▶ In practice, we usually want to obtain the Fourier transform using digital computation, thus needing:
  - ▶ finite signal length
  - ▶ finite set of frequencies
- ▶ The DFT provides a mean for achieving this!

## From the DTFT to the DFT

- ▶ We start from the DTFT definition

$$X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x(n)e^{-j\omega n},$$

which is a  $2\pi$  periodic continuous function of  $\omega$

- ▶ We sample it at  $N$  uniformly spaced samples between 0 and  $2\pi$  (sample frequency equal to an integer multiple of its period), i.e.

$$\omega_k = \frac{2\pi}{N}k, \quad k \in \mathbb{Z}$$

- ▶ The sampling process leads to

$$X'(e^{j\omega}) = X(e^{j\omega}) \sum_{k=-\infty}^{\infty} \delta\left(\omega - \frac{2\pi}{N}k\right)$$

## From the DTFT to the DFT (cont')

- ▶ We apply the convolution theorem for the DTFT, obtaining

$$x'(n) = \text{DTFT}^{-1} \left\{ X'(e^{j\omega}) \right\} = x(n) * \text{DTFT}^{-1} \left\{ \sum_{k=-\infty}^{\infty} \delta \left( \omega - \frac{2\pi}{N} k \right) \right\}$$

- ▶ It can be proved that

$$\text{DTFT}^{-1} \left\{ \sum_{k=-\infty}^{\infty} \delta \left( \omega - \frac{2\pi}{N} k \right) \right\} = \frac{N}{2\pi} \sum_{p=-\infty}^{\infty} \delta(n - Np)$$

- ▶ Finally we have:

$$x'(n) = x(n) * \frac{N}{2\pi} \sum_{p=-\infty}^{\infty} \delta(n - Np) = \frac{N}{2\pi} \sum_{p=-\infty}^{\infty} x(n - Np)$$

## From the DTFT to the DFT (cont')

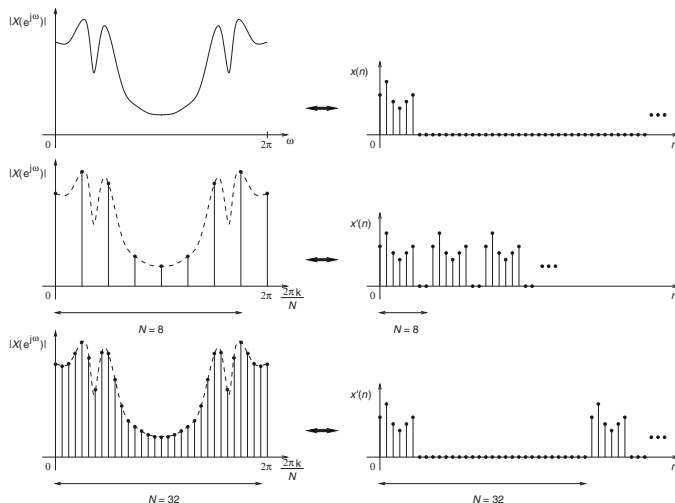
- ▶ The last equation indicates that, from a sampled DTFT, we can recover a signal  $x'(n)$  consisting of a sum of periodic replicas of the original discrete signal  $x(n)$
- ▶ This means that, in order to exactly recover  $x(n)$  (by isolating a single repetition), its length  $L$  must be not greater than  $N$ 
  - ▶ in other words, we require the signal  $x(n)$  to be *time-limited*
  - ▶ this is the equivalent of the sampling theorem, applied to sampling in the frequency domain
- ▶ Therefore, if  $L \leq N$ , we can recover the signal as

$$x(n) = \frac{2\pi}{N} x'(n), \quad \text{for } 0 \leq n \leq N-1$$

- ▶ If  $L > N$  the replicas overlap, thus introducing *time-domain aliasing*

## From the DTFT to the DFT (cont')

Example: sampling the DTFT with a different number of samples  $N$  and its effect in the time-domain:



## From the DTFT to the DFT (cont')

From the previous picture, we observe that:

- ▶ sampling the DTFT corresponds to generating replicas of the original signal in the time domain
- ▶ increasing the number of samples  $N$  corresponds to increase the distance between replicas in the time domain
- ▶ clearly, in order to avoid that the replicas overlap, we must satisfy  $N \geq L$  (sampling theorem)



# The Discrete Fourier Transform (DFT) and its inverse (IDFT)

- ▶ Considering a signal  $x(n)$  of length  $N$ , its DFT is defined as

$$X(k) \triangleq \sum_{n=0}^{N-1} x(n) e^{-j \frac{2\pi kn}{N}}, \quad \text{for } 0 \leq k \leq N-1$$

- ▶ The IDTFT is computed as

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j \frac{2\pi kn}{N}}, \quad \text{for } 0 \leq n \leq N-1$$

## DFT periodicity

The DFT can be seen as a periodic transform in both frequency and time domain

► **Frequency domain:**

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j \frac{2\pi kn}{N}} = X(k + mN), \quad \text{for } m \in \mathbb{Z},$$

corresponding to the fact that we are sampling the DTFT, which is itself  $2\pi$ -periodic

► **Time domain:**

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j \frac{2\pi kn}{N}} = x(n + mN), \quad \text{for } m \in \mathbb{Z},$$

corresponding to the fact that sampling the DTFT means introducing replicas in the time domain

## DFT periodicity: modulo indexing

- ▶ A convenient way to account for periodicity is to consider the periodic extensions using modulo indexing
- ▶ We will use the following notation:
  - ▶  $X(k)_N \triangleq X(k \bmod N)$  for the frequency domain
  - ▶  $x(n)_N \triangleq x(n \bmod N)$  for the time domain
- ▶ Remember that all the operations involving the DFT/IDFT are implicitly circular (modulo  $N$ )!

# Properties of the DFT

- ▶ Most of the properties of the DFT are analogous to those of the DTFT
- ▶ However, we must pay attention to the fact that, **for all the operations involving shifts, modulo  $N$  indexing must be considered**

## Properties of the DFT (cont')

### ► **Linearity**

$$k_1x_1(n) + k_2x_2(n) \quad \longleftrightarrow \quad k_1X_1(k) + k_2X_2(k)$$

## Properties of the DFT (cont')

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### ► Time-reversal

$$x(-n)_N \longleftrightarrow X(-k)_N$$

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- ▶ **Frequency-shift theorem**

$$e^{j\omega_k l} x(n) \longleftrightarrow X(k+l)_N$$



## Properties of the DFT (cont')

### ► Circular convolution in time

$$\sum_{l=0}^{N-1} x(l)h(n-l)_N = \sum_{l=0}^{N-1} x(n-l)_N h(l) \quad \longleftrightarrow \quad X(k)H(k)$$

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### ► Correlation

$$\sum_{l=0}^{N-1} x(l)h(n+l)_N \quad \longleftrightarrow \quad X(-k)_N H(k)$$

### ► Parseval's theorem

$$\sum_{n=0}^{N-1} |x(n)|^2 = \frac{1}{N} \sum_{n=0}^{N-1} |X(k)|^2$$

## Properties of the DFT (cont')

- ▶ When  $x(n)$  is a **real sequence**:

$$\operatorname{Re}\{X(k)\} = \operatorname{Re}\{X(-k)_N\}$$

$$\operatorname{Im}\{X(k)\} = -\operatorname{Im}\{X(-k)_N\}$$

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- ▶ When  $x(n)$  is an **imaginary sequence**:

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## Symmetry properties (cont')

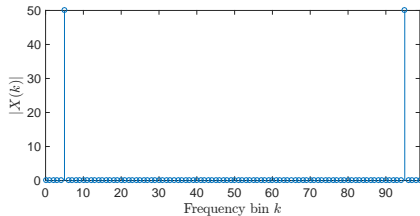
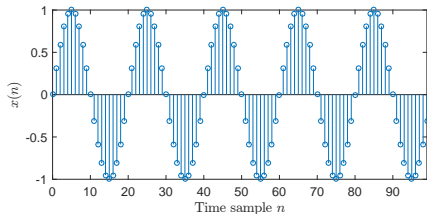
- Using the above definitions, the following symmetry properties hold:

$x(n)$		$X(k)$
real and even	$\longleftrightarrow$	real and even
imaginary and even	$\longleftrightarrow$	imaginary and even
real and odd	$\longleftrightarrow$	imaginary and odd
imaginary and odd	$\longleftrightarrow$	real and odd
conjugate symmetric	$\longleftrightarrow$	real

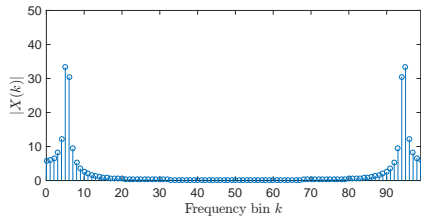
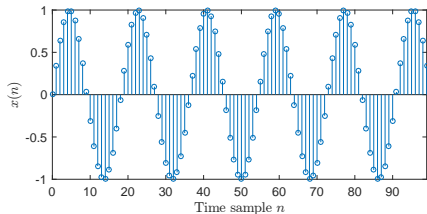
# DFT: spectral leakage

**Example:** DFT of sinusoid segment of length  $N = 100$ ,  $x(n) = \sin(2\pi an/N)$

Integer  $a$  ( $a = 5$ )



Non integer  $a$  ( $a = 5.5$ )



## DFT: spectral leakage (cont')

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- ▶ Only the DFT sinusoids are not cut off at the window boundaries
- ▶ To understand spectral leakage, remember that taking the DFT means computing samples of the DTFT of infinite periodic extension of the considered  $N$ -samples time window:
  - ▶ discontinuities at the end of repeated blocks
  - ▶ these “glitches” every  $N$  samples can be considered as a source of new energy over the entire spectrum

## Reducing the spectral leakage: windowing

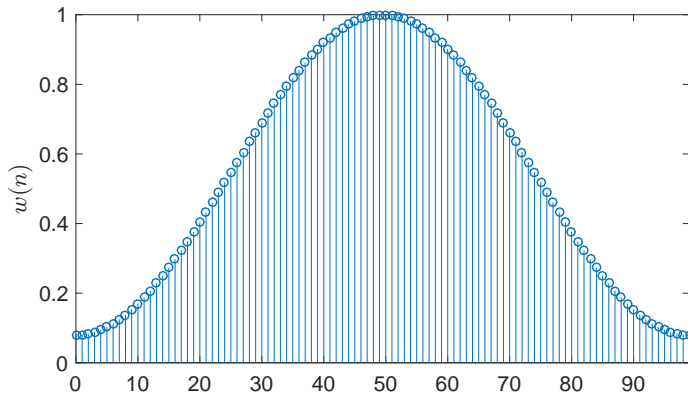
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## Reducing the spectral leakage: windowing

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- ▶ A typical window is the “raised cosine” one (aka *Hamming window*), which tapers data gracefully to zero at both endpoints:

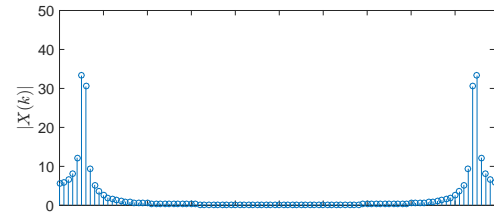
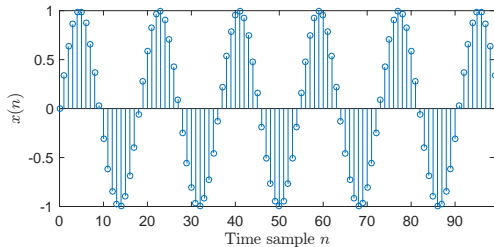
$$w_H(n) = 0.54 + 0.46 \cos \left[ \frac{2\pi(n - N/2)}{N} \right] , \quad n = 0, 1, \dots, N - 1$$



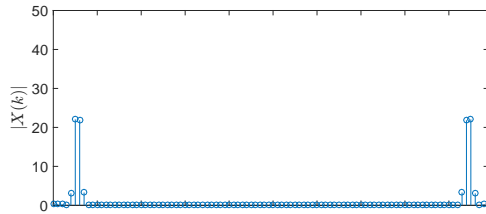
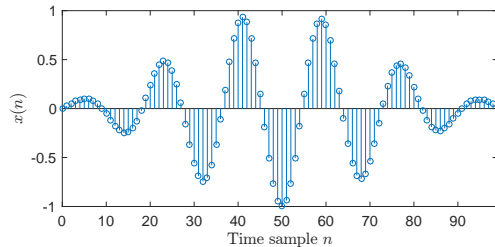
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Non-tapered ( $a = 5.5$ )

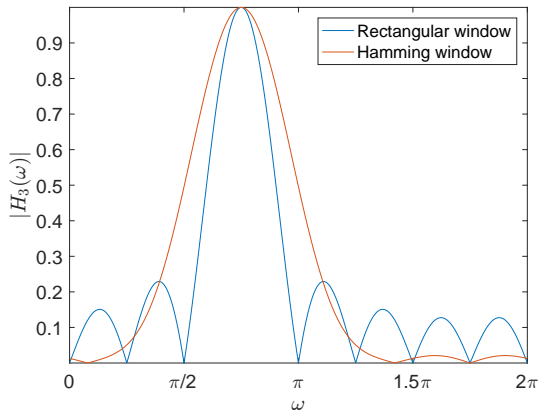


Tapered ( $a = 5.5$ )



## Reducing the spectral leakage: windowing (cont')

- ▶ Using a tapered window, the mainlobe widens and the sidelobes decrease in the DFT response
- ▶ Using no windows is the same of using a rectangular window
- ▶ Example for  $N = 8$ ,  $k = 3$ :



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- ▶ It turns that an impulse (i.e., the ideal Fourier transform of a sinusoid) is spread into a sinc-like function
- ▶ In other words, the **spectral resolution depends on the width of the main lobe** of the sinc function
  - ▶ what happens if more than one sinusoidal component are present in the signal?

## DFT spectral resolution (cont')

- ▶ Consider a signal containing two sinusoidal components at frequencies  $\omega_a$  and  $\omega_b$ , truncated with a  $N$ -length rectangular window:

$$x(n) = [e^{j\omega_a n} + e^{j\omega_b n}] \cdot w_R(n)$$



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$$\begin{aligned} X(k) &\triangleq X(e^{j\omega}) \Big|_{\omega=\omega_k} \\ &= \left( [\delta(\omega - \omega_a) + \delta(\omega - \omega_b)] * \frac{1 - e^{-j\omega N}}{1 - e^{-j\omega}} \right) \Big|_{\omega=\omega_k} \end{aligned}$$

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- ▶ The two impulses at frequencies  $\omega_a$  and  $\omega_b$  turn to be blurred due to the convolution:
  - ▶ it may happen that  $\omega_a$  and  $\omega_b$  are too close and the frequency resolution provided by the DFT is not enough
  - ▶ in this case we are not able to resolve the two frequency components! (see example on the next slide)

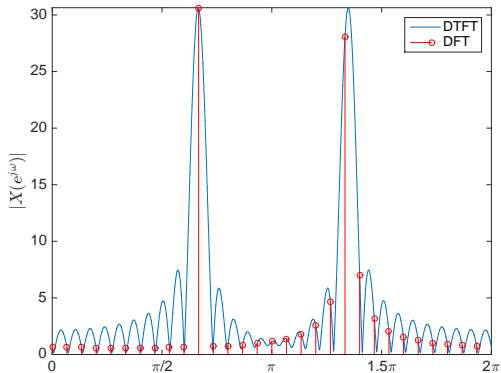
## DFT spectral resolution (cont')

**Example:** two complex sinusoids with freq. distance  $\Delta_\omega = |\omega_a - \omega_b|$ ,  $N = 30$

Case 1:  $\Delta_\omega = 10.2 \times 2\pi/N$

►  $\omega_a = 10 \times 2\pi/N$

►  $\omega_b = 20.2 \times 2\pi/N$



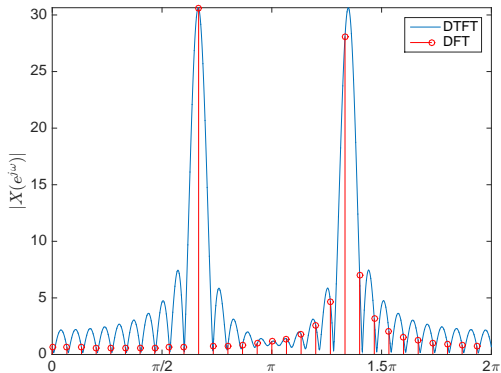
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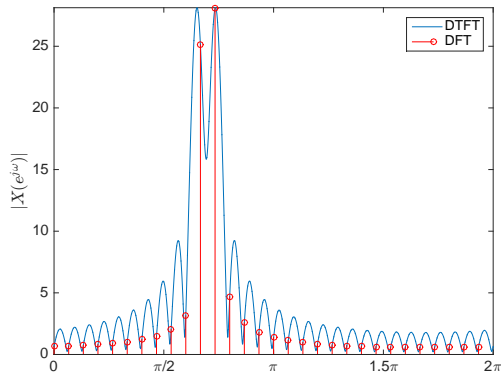
►  $\omega_b = 20.2 \times 2\pi/N$



Case 2:  $\Delta\omega = 0.8 \times 2\pi/N$

►  $\omega_a = 10 \times 2\pi/N$

►  $\omega_b = 10.8 \times 2\pi/N$



## DFT spectral resolution (cont')

- ▶ Clearly, the spectral resolution is governed by the choice of the segment length  $N$ , which determines the distance between two adjacent frequency bins:

$$\omega_k - \omega_{k-1} = \frac{2\pi}{N}, \quad k = 1, \dots, N-1$$

- ▶ If the two ideal impulses at frequencies  $\omega_a$  and  $\omega_b$  fall inside the mainlobe of the DFT response, they will be “absorbed” in a single, wider “blurred” peak

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- ▶ If the two ideal impulses at frequencies  $\omega_a$  and  $\omega_b$  fall inside the mainlobe of the DFT response, they will be “absorbed” in a single, wider “blurred” peak
- ▶ In order to guarantee an effective separation of the two frequency components  $\omega_a$  and  $\omega_b$ , we must ensure that:

$$\Delta\omega = |\omega_a - \omega_b| > 2 \times \frac{2\pi}{N}$$

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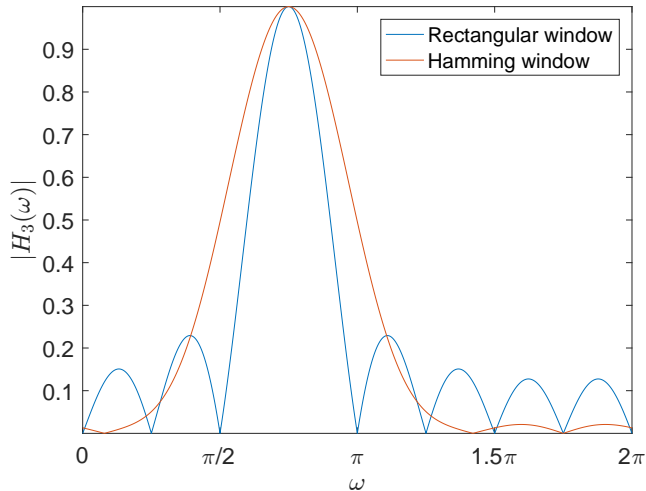
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- ▶ In general, we can say that the “blurring” of the impulses is determined by the shape of the DTFT of the chosen window
- ▶ To be more precise, the **spectral resolution depends on the width  $B_\omega$  of the mainlobe of the observation window**:
  - ▶  $B_\omega = \frac{4\pi}{N}$  for rectangular window (i.e., no windowing)
  - ▶  $B_\omega = \frac{8\pi}{N}$  for Hamming's window
  - ▶ ... (there exists a number of different windows!)

## DFT spectral resolution: the general case (cont')

Recall the previous example (DFT response for  $N=8$ ,  $k=3$ ):



## DFT spectral resolution: the general case (cont')

- ▶ The general formula for guaranteeing spectral separation is

$$\Delta_{\omega} > B_{\omega} = Q \times \frac{2\pi}{N} ,$$

where  $Q$  is a constant depending on the type of window (e.g.,  $Q = 2$  for rectangular window,  $Q = 4$  for Hamming window)

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To conclude:

The **spectral resolution** of the DFT is **governed by the width of the mainlobe** of the used window, and **increases by increasing the window length  $N$** .

## DFT interpolation via zero-padding

- ▶ Let us go back for a while to the DFT definition:

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi kn}{N}}, \quad 0 \leq k \leq N-1$$

- ▶ Suppose that we want to compute an  $N$ -points DFT but the signal length is  $L < N$

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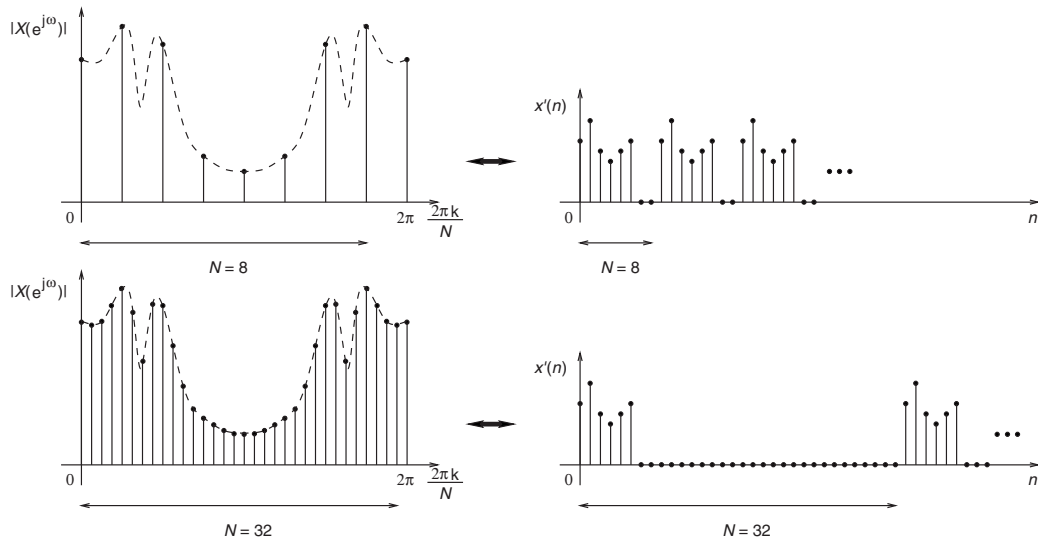
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- ▶ Note that:
  - ▶ adding an infinite number of zeros than  $N \rightarrow \infty$ : this corresponds to computing the DTFT
  - ▶ roughly speaking, by increasing  $N$  (i.e., by appending more zeros), we provide a better approximation of the DTFT

# DFT interpolation via zero-padding (cont')

Example:



## DFT interpolation via zero-padding (cont')

In the picture, the signal has a length  $L = 6$ . The DFT is computed with  $N = 8$  and with  $N = 32$ , and we observe that:

- ▶ the larger the number of zeros padded on  $x(n)$  for the calculation of the DFT, the more it resembles its DTFT. This happens because of the larger number of samples taken within  $[0, 2\pi]$
- ▶ the larger the amount of zero-padding the greater the computational and storage requirements involved in the DFT computation

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To conclude:

**Zero-padding acts as an interpolator in the frequency domain**

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- ▶ Zero-padding is effective to interpolate between frequency bins of the DFT
- ▶ **What is the effect of zero-padding on spectral resolution?**
  - ▶ Answer: **NOTHING!**
  - ▶ Indeed, adding zeros we are not really increasing the segment length!
  - ▶ i.e., no further information is added to the analyzed segment!

## Summary on interpolation, windowing and spectral resolution

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  - ▶ resolution can be always increased by increasing the window length  $N$
- ▶ **Interpolation:**
  - ▶ zero-padding corresponds to interpolating in the DFT domain
  - ▶ it **increases** the available **frequency bins**, but the **spectral resolution remains unaltered**: it does not increase the capability of resolving close sinusoidal peaks

# Review: road map to Fourier Kingdom

	<b><i>APERIODIC</i> in time</b> <b><i>CONTINUOUS</i> in frequency</b>	<b><i>PERIODIC</i> in time</b> <b><i>DISCRETE</i> in frequency</b>
<b><i>CONTINUOUS</i> in time</b> <b><i>APERIODIC</i> in frequency</b>	Fourier Transform  $X(j\Omega) = \int_{-\infty}^{\infty} x(t)e^{-j\Omega t} dt$ $x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(j\Omega)e^{j\Omega t} d\Omega$	Fourier Series  $a_k = \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)e^{-j\frac{2\pi k t}{T}} dt$ $x(t) = \sum_{k=-\infty}^{\infty} a_k e^{j\frac{2\pi k t}{T}}$
<b><i>DISCRETE</i> in time</b> <b><i>PERIODIC</i> in frequency</b>	Discrete-Time Fourier Transform (DTFT)  $X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x(n)e^{-j\omega n}$ $x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega})e^{j\omega n} d\omega$	Discrete Fourier Transform (DFT)  $X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi k n}{N}}$ $x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k)e^{j\frac{2\pi k n}{N}}$