



The Frequency Domain

DS-GA 1013 / MATH-GA 2824 Optimization-based Data Analysis

http://www.cims.nyu.edu/~cfgranda/pages/OBDA_fall17/index.html

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Fourier Representations

Sampling theorem

Convolution

Wiener deconvolution

Complex Exponential

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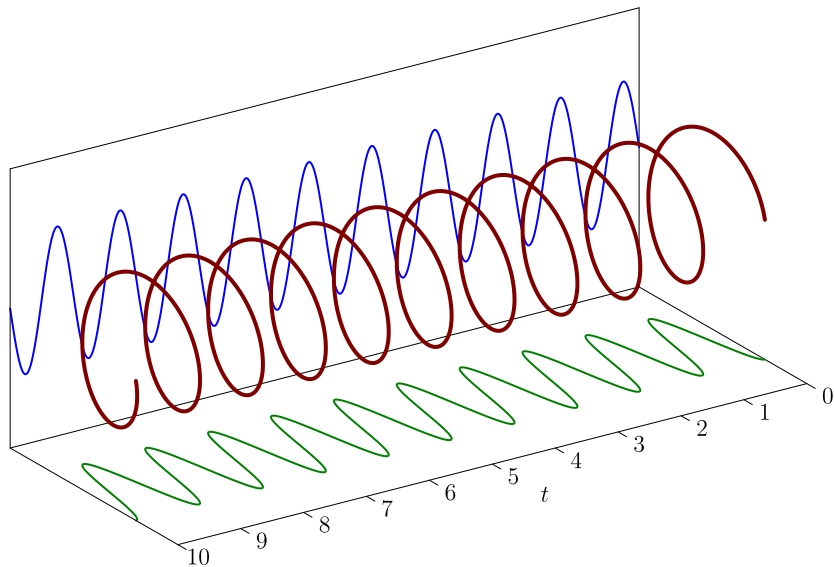
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Complex Exponential: $\exp(2\pi ix)$ for $x \in [0, 10]$



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4. The family of functions h_k , for $k \in \mathbb{Z}$, form an orthonormal set of functions in $\mathcal{L}_2[-1/2, 1/2]$

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Fourier Series

1. We assume $f : [-1/2, 1/2] \rightarrow \mathbb{C}$ with $f \in \mathcal{L}_2[-1/2, 1/2]$ and $f(-1/2) = f(1/2)$. This corresponds to 1-periodic functions.
2. We define the Fourier series of f , denoted $S\{f\}$, by

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4. Convergence of Fourier Series:

$$\left\| f - \sum_{k=-n}^n F[k] h_k \right\|_{\mathcal{L}_2} \rightarrow 0,$$

as $n \rightarrow \infty$. If f is also continuously differentiable the convergence is uniform.

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Proof: Computing we have

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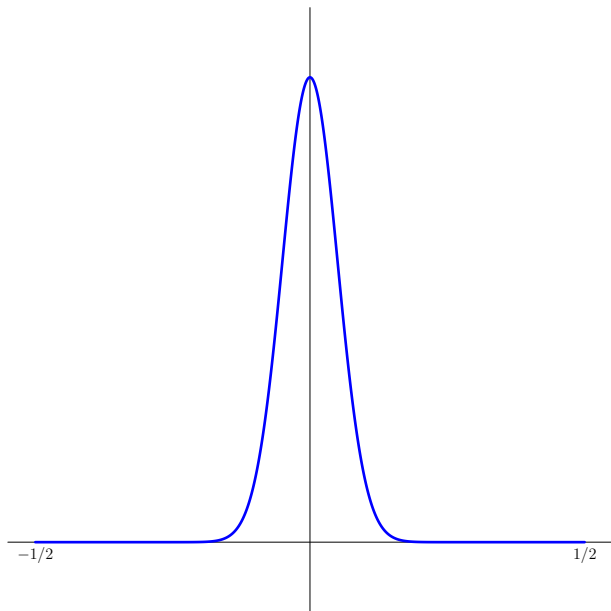
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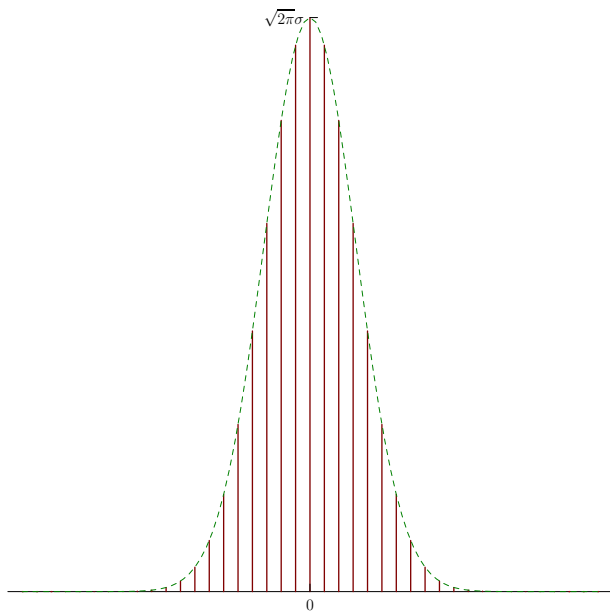
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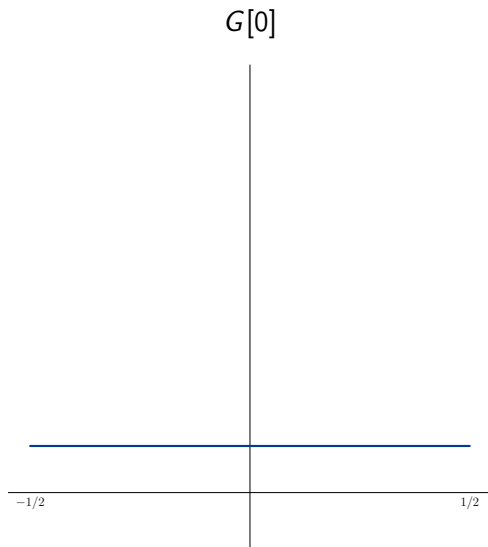
Examples of Fourier Series: Gaussian Plot $g(t)$



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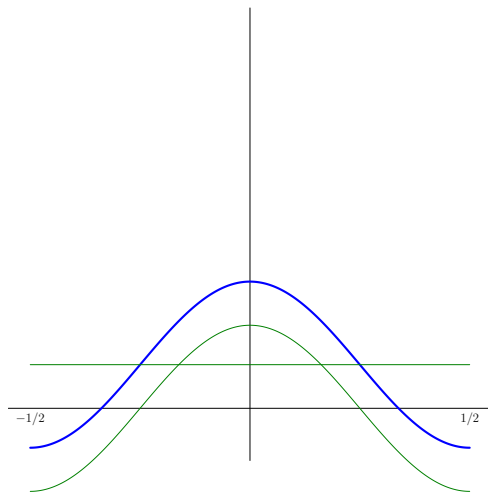


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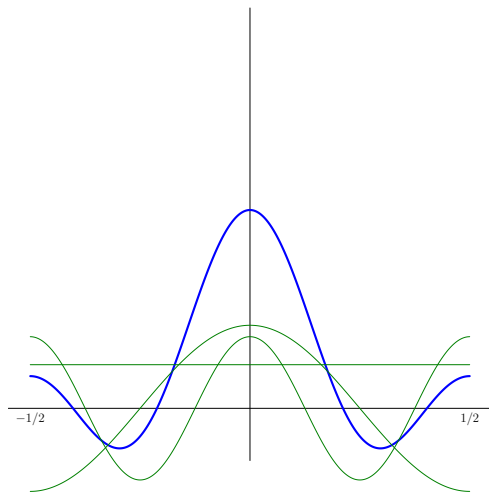
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$$G[0] + G[1]e^{2\pi it} + G[-1]e^{-2\pi it} = G[0] + 2G[1]\cos(2\pi t)$$



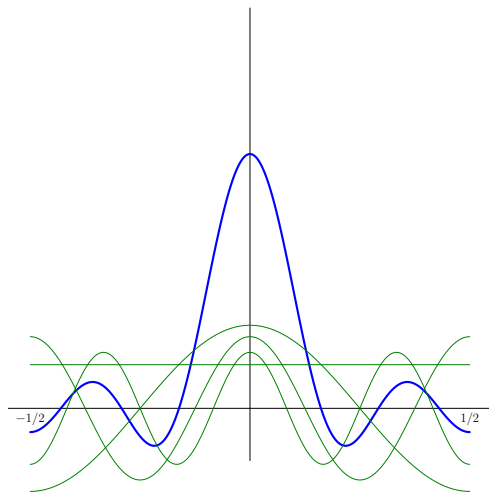
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$$\sum_{k=-2}^2 G[k]e^{2\pi ikt} = G[0] + \sum_{k=1}^2 2G[k] \cos(2\pi kt)$$



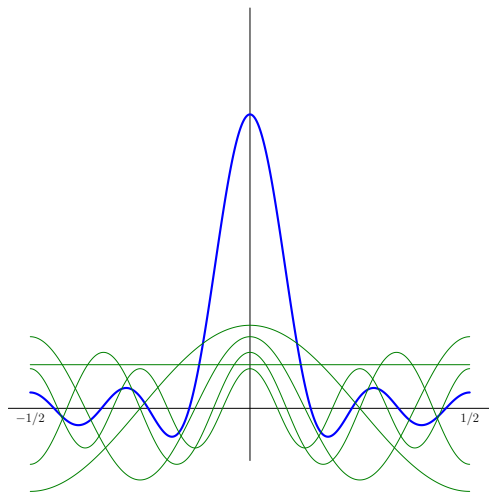
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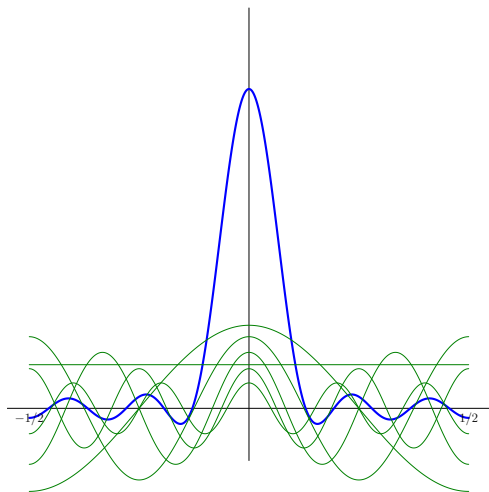
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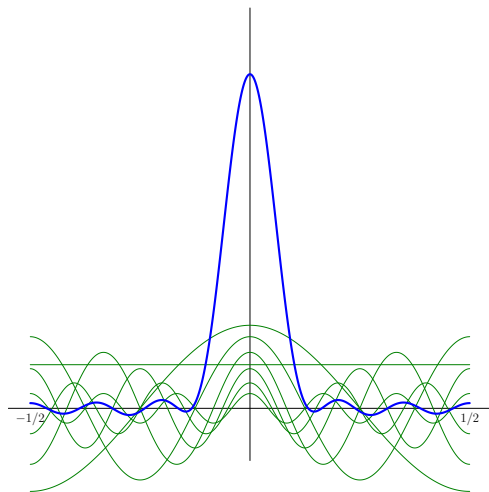
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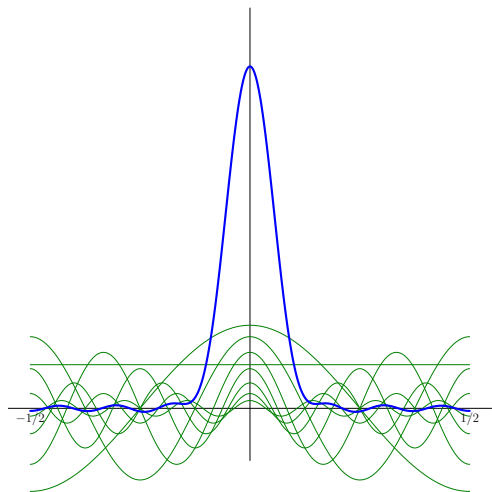
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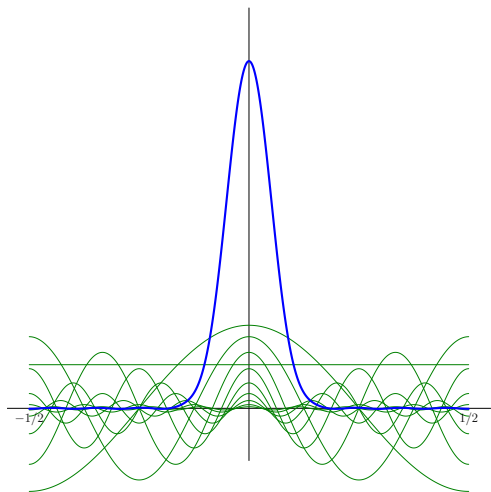
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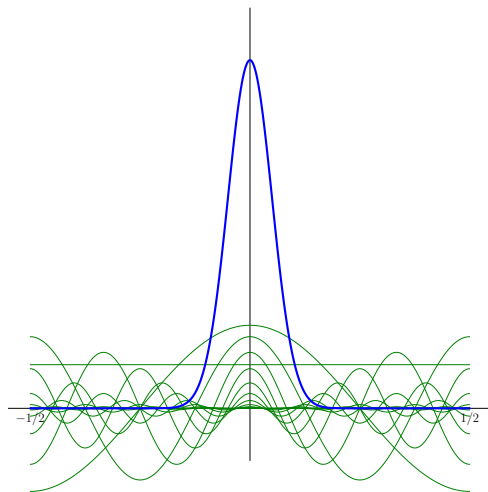
Examples of Fourier Series: Gaussian Plot $g(t)$

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Examples of Fourier Series: Gaussian Plot $g(t)$

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Examples of Fourier Series: Dirichlet Kernel

1. Consider a function $d_{k_c}(t)$ with Fourier coefficients $D_{k_c}(k)$ given by

$$D_{k_c}[k] = \begin{cases} 1 & \text{if } |k| \leq k_c, \\ 0 & \text{otherwise.} \end{cases}$$

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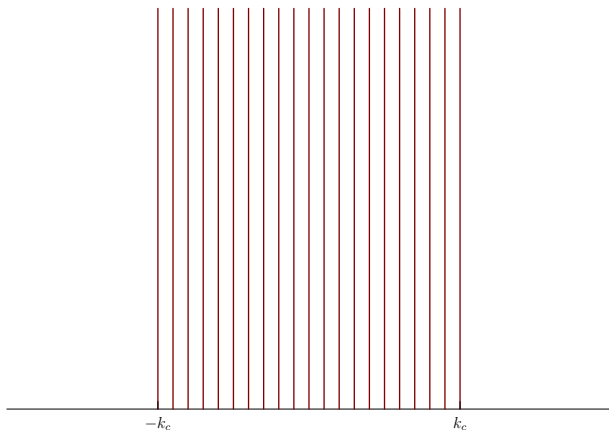
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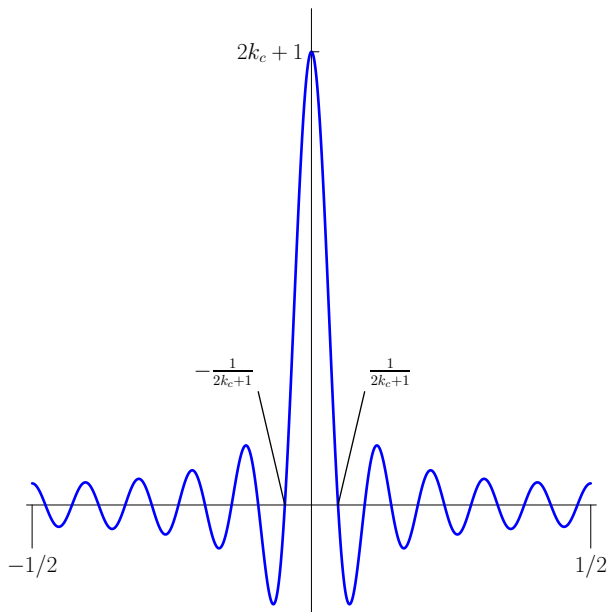
$$d_{k_c}(t) = \frac{\sin((2k_c + 1)\pi t)}{\sin(\pi t)},$$

for $t \neq 0$ and $d_{k_c}(0) = 2k_c + 1$.

Examples of Fourier Series: Dirichlet Plot $D_{k_c}[k]$



Examples of Fourier Series: Dirichlet Plot $d_{k_c}(t)$



Discrete Complex Sinusoids

1. Define the discrete complex sinusoid $\vec{h}_k^{[n]} \in \mathbb{C}^n$ by

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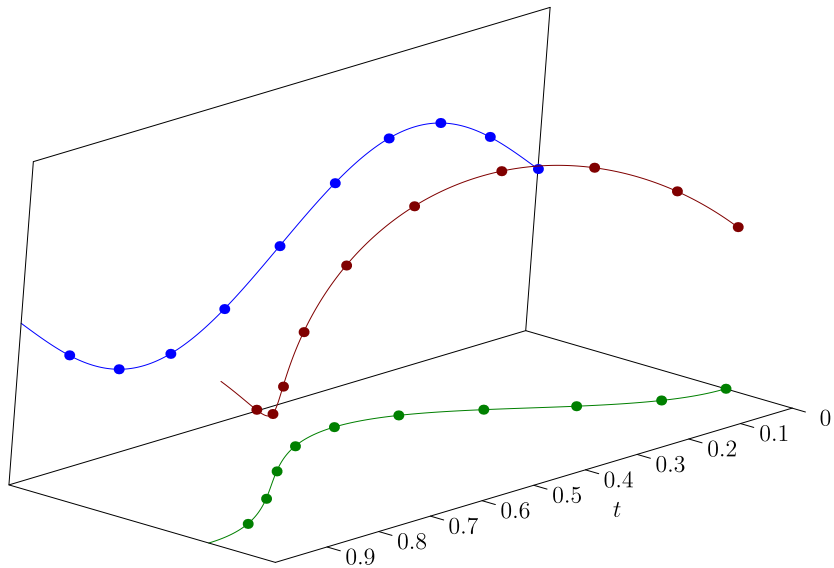
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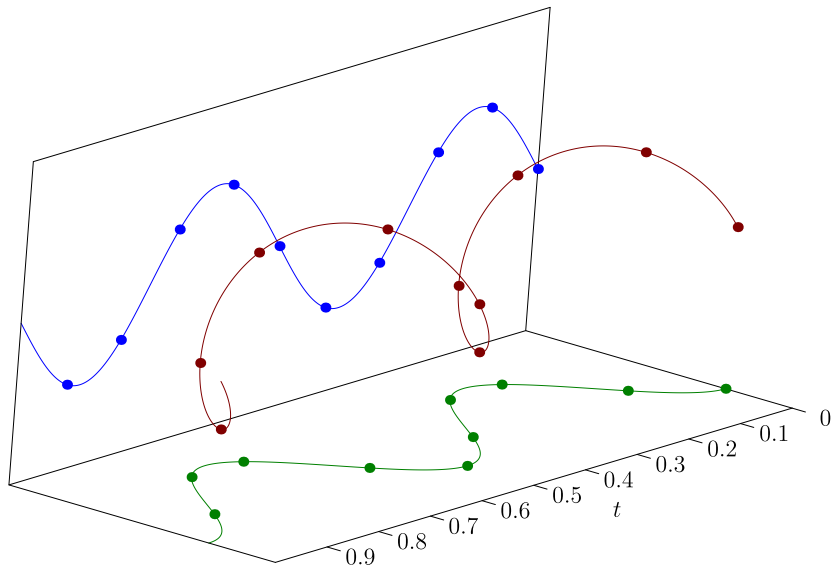
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3. Formed by sampling h_k with every $1/n$ time units.

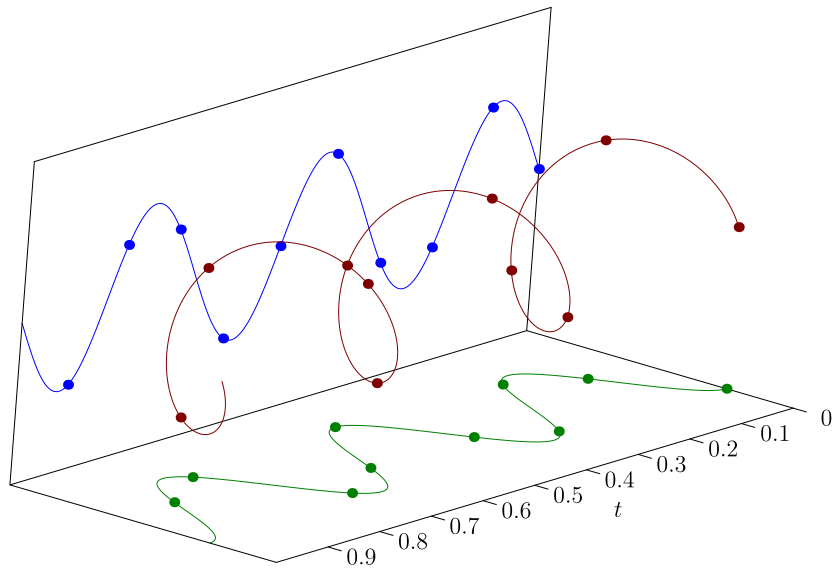
Discrete Complex Sinusoids: $\vec{h}_1^{[10]}$



Discrete Complex Sinusoids: $\vec{h}_2^{[10]}$



Discrete Complex Sinusoids: $\vec{h}_3^{[10]}$



Discrete Complex Sinusoids: Orthogonal

The discrete complex sinusoids $\frac{1}{\sqrt{n}} \vec{h}_0^{[n]}, \dots, \frac{1}{\sqrt{n}} \vec{h}_{n-1}^{[n]}$ form an orthonormal basis of \mathbb{C}^n .

Discrete Complex Sinusoids: Unit norm

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Discrete Complex Sinusoids: Unit norm

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$$\begin{aligned}\|\vec{h}_k^{[n]}\|_2^2 &= \sum_{j=0}^{n-1} \left| \vec{h}_k^{[n]}[j] \right|^2 \\ &= \sum_{j=0}^{n-1} 1\end{aligned}$$

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Properties of Discrete Complex Sinusoids: DFT

1. Any vector of samples $\vec{x} \in \mathbb{C}^n$ can be written as a linear combination of the orthonormal basis vectors $\frac{1}{\sqrt{n}}\vec{h}_0^{[n]}, \dots, \frac{1}{\sqrt{n}}\vec{h}_{n-1}^{[n]}$:

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2. We define the discrete Fourier coefficient $\vec{X}[k] := a_k$.

Properties of Discrete Complex Sinusoids: DFT

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$$\vec{x} =: \sum_{k=0}^n a_k \vec{h}_k^{[n]},$$

for some $a_k \in \mathbb{C}$.

2. We define the discrete Fourier coefficient $\vec{X}[k] := a_k$.
3. Define the DFT (Discrete Fourier Transform) matrix $W \in \mathbb{C}^{n \times n}$ by

$$W = \left[\begin{array}{c|c|c|c} \hline & & & \\ \hline \vec{h}_0^{[n]} & \vec{h}_1^{[n]} & \dots & \vec{h}_{n-1}^{[n]} \\ \hline & & & \\ \hline \end{array} \right]^*$$

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4. Note that $\frac{1}{\sqrt{n}}W$ is unitary.

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4. Note that $\frac{1}{\sqrt{n}}W$ is unitary.
5. $\vec{x} = \frac{1}{n}W^*\vec{X}$ and $\vec{X} = W\vec{x}$

Properties of Discrete Complex Sinusoids: DFT

1. Runtime to apply DFT matrix to \vec{x} to obtain \vec{X} is $O(n^2)$.

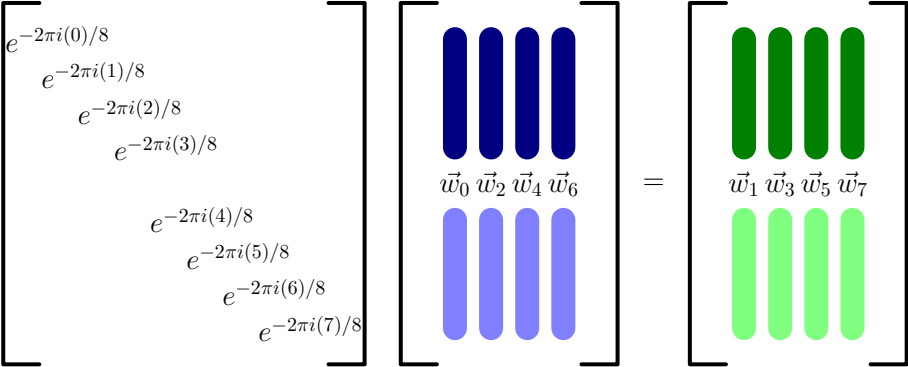
Properties of Discrete Complex Sinusoids: DFT

1. Runtime to apply DFT matrix to \vec{x} to obtain \vec{X} is $O(n^2)$.
2. How can we improve this time? Exploit symmetry.

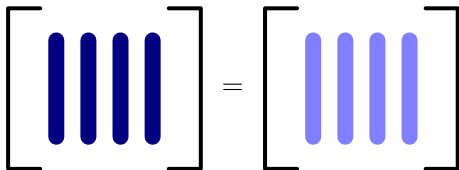
Discrete Complex Sinusoids: FFT

$$\begin{bmatrix} \vec{X}[0] \\ \vec{X}[1] \\ \vec{X}[2] \\ \vec{X}[3] \\ \vec{X}[4] \\ \vec{X}[5] \\ \vec{X}[6] \\ \vec{X}[7] \end{bmatrix} = \begin{bmatrix} \vec{w}_0 & \vec{w}_1 & \vec{w}_2 & \vec{w}_3 & \vec{w}_4 & \vec{w}_5 & \vec{w}_6 & \vec{w}_7 \\ \vec{w}_0 & \vec{w}_1 & \vec{w}_2 & \vec{w}_3 & \vec{w}_4 & \vec{w}_5 & \vec{w}_6 & \vec{w}_7 \end{bmatrix} \begin{bmatrix} \vec{x}[0] \\ \vec{x}[1] \\ \vec{x}[2] \\ \vec{x}[3] \\ \vec{x}[4] \\ \vec{x}[5] \\ \vec{x}[6] \\ \vec{x}[7] \end{bmatrix}$$

Discrete Complex Sinusoids: FFT



Discrete Complex Sinusoids: FFT


$$\left[\begin{array}{c} \text{dark blue bar} \\ \text{dark blue bar} \\ \text{dark blue bar} \\ \text{dark blue bar} \end{array} \right] = \left[\begin{array}{c} \text{light blue bar} \\ \text{light blue bar} \\ \text{light blue bar} \\ \text{light blue bar} \end{array} \right]$$

Discrete Complex Sinusoids: FFT

$$\begin{bmatrix} \vec{X}[0] \\ \vec{X}[1] \\ \vec{X}[2] \\ \vec{X}[3] \end{bmatrix} = \begin{bmatrix} \text{||||} \\ \text{||||} \\ \text{||||} \\ \text{||||} \end{bmatrix} \begin{bmatrix} x[0] \\ x[2] \\ x[4] \\ x[6] \end{bmatrix} + \begin{bmatrix} e^{-2\pi i(0)/8} \\ e^{-2\pi i(1)/8} \\ e^{-2\pi i(2)/8} \\ e^{-2\pi i(3)/8} \end{bmatrix} \begin{bmatrix} \text{||||} \\ \text{||||} \\ \text{||||} \\ \text{||||} \end{bmatrix} \begin{bmatrix} x[1] \\ x[3] \\ x[5] \\ x[7] \end{bmatrix}$$
$$\begin{bmatrix} \vec{X}[4] \\ \vec{X}[5] \\ \vec{X}[6] \\ \vec{X}[7] \end{bmatrix} = \begin{bmatrix} \text{||||} \\ \text{||||} \\ \text{||||} \\ \text{||||} \end{bmatrix} \begin{bmatrix} \vec{x}[0] \\ \vec{x}[2] \\ \vec{x}[4] \\ \vec{x}[6] \end{bmatrix} + \begin{bmatrix} e^{-2\pi i(4)/8} \\ e^{-2\pi i(5)/8} \\ e^{-2\pi i(6)/8} \\ e^{-2\pi i(7)/8} \end{bmatrix} \begin{bmatrix} \text{||||} \\ \text{||||} \\ \text{||||} \\ \text{||||} \end{bmatrix} \begin{bmatrix} \vec{x}[1] \\ \vec{x}[3] \\ \vec{x}[5] \\ \vec{x}[7] \end{bmatrix}$$

Discrete Complex Sinusoids: FFT

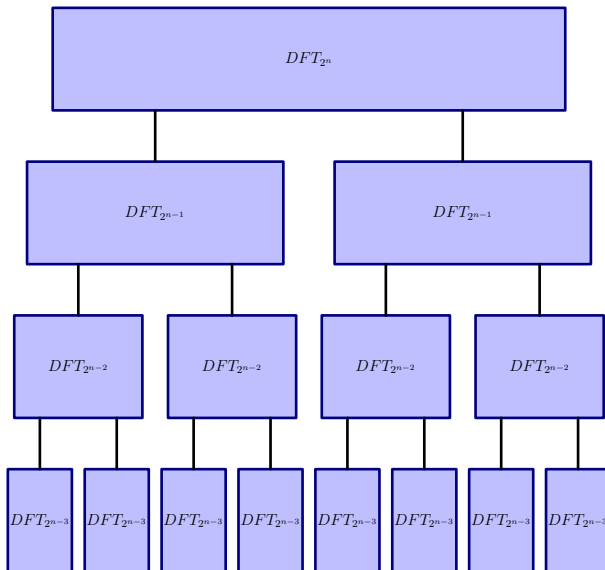
If $n = 1$, then set $\text{DFT}^1(\vec{x}) := \vec{x}$, otherwise apply the following steps:

1. Compute $\text{DFT}^{[n/2]}(\vec{x}_{\text{even}})$.
2. Compute $\text{DFT}^{[n/2]}(\vec{x}_{\text{odd}})$.
3. For $k = 1, 2, \dots, n/2$ set

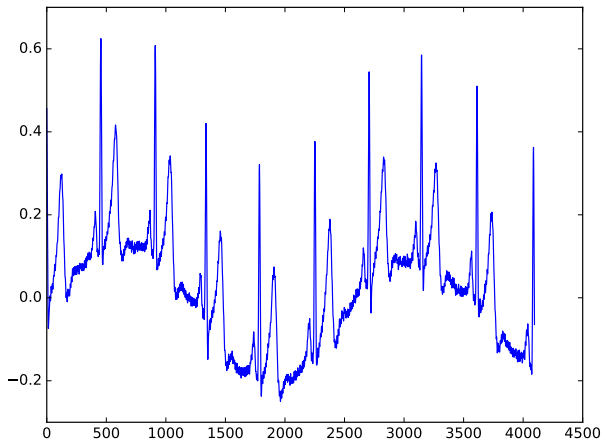
$$\text{DFT}^{[n]}(\vec{x})_k := \text{DFT}^{[n/2]}(\vec{x}_{\text{even}})_k + \exp\left(-\frac{i2\pi k}{n}\right) \text{DFT}^{[n/2]}(\vec{x}_{\text{odd}})_k,$$

$$\text{DFT}^{[n]}(\vec{x})_{k+n/2} := \text{DFT}^{[n/2]}(\vec{x}_{\text{even}})_k - \exp\left(-\frac{i2\pi k}{n}\right) \text{DFT}^{[n/2]}(\vec{x}_{\text{odd}})_k.$$

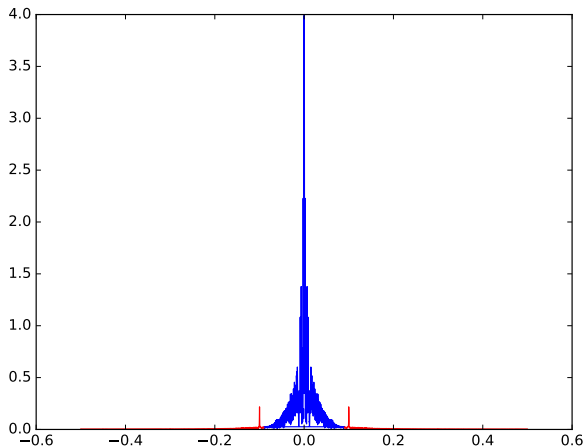
Discrete Complex Sinusoids: FFT



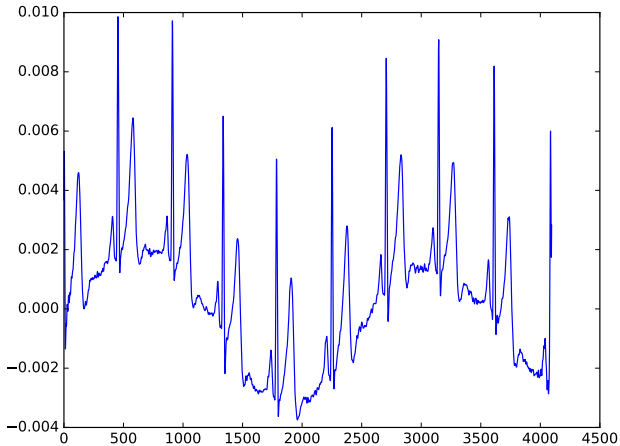
Discrete Complex Sinusoids: ECG



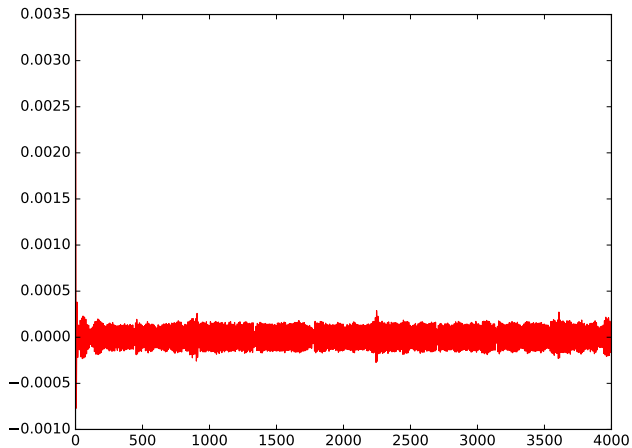
Discrete Complex Sinusoids: ECG



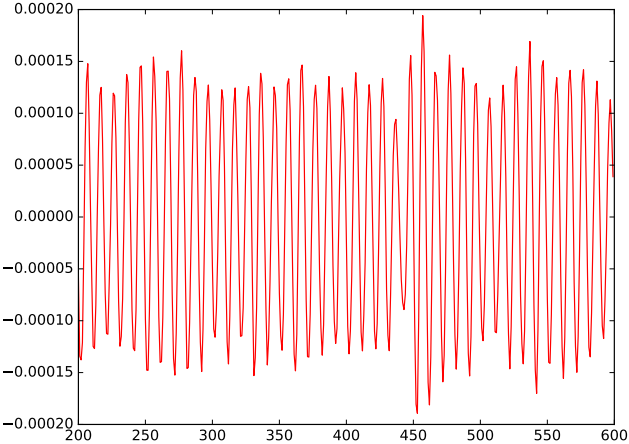
Discrete Complex Sinusoids: ECG



Discrete Complex Sinusoids: ECG



Discrete Complex Sinusoids: ECG



Two-dimensional DFT

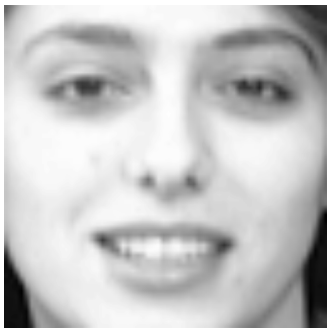
The 2D DFT \widehat{M} of an image $M \in \mathbb{C}^{n \times n}$ is given by

$$\widehat{M}[k_1, k_2] := \left\langle M, \vec{h}_{k_1, k_2}^{2D} \right\rangle, \quad 0 \leq k_1, k_2 \leq n-1$$

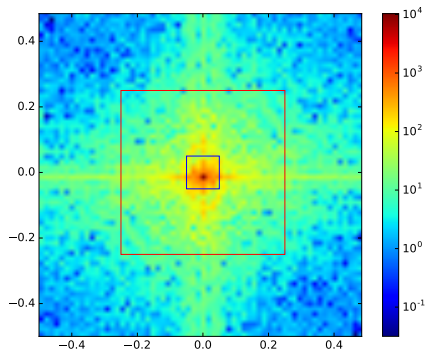
$$\begin{aligned} \vec{h}_{k_1, k_2}^{2D} &:= \vec{h}_{k_1}^{[n]} \left(\vec{h}_{k_2}^{[n]} \right)^T \\ &= \begin{bmatrix} 1 & e^{\frac{i2\pi k_2}{n}} & \cdots & e^{\frac{i2\pi k_2(n-1)}{n}} \\ e^{\frac{i2\pi k_1}{n}} & e^{\frac{i2\pi(k_1+k_2)}{n}} & \cdots & e^{\frac{i2\pi(k_1+k_2(n-1))}{n}} \\ \cdots & \cdots & \cdots & \cdots \\ e^{\frac{i2\pi k_1(n-1)}{n}} & e^{\frac{i2\pi(k_1(n-1)+k_2)}{n}} & \cdots & e^{\frac{i2\pi(k_1(n-1)+k_2(n-1))}{n}} \end{bmatrix} \end{aligned}$$

$$\widehat{M} = WMW$$

Two-dimensional DFT



Log. of magnitude of 2D DFT



Two-dimensional DFT

Low-pass component



Band-pass component



High-pass component



Discrete cosine transform (DCT)

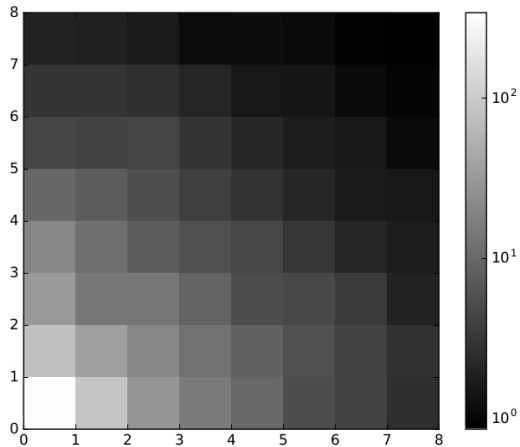
Variant of DFT for **real** signals

Signal is interpreted as one half of a symmetric signal

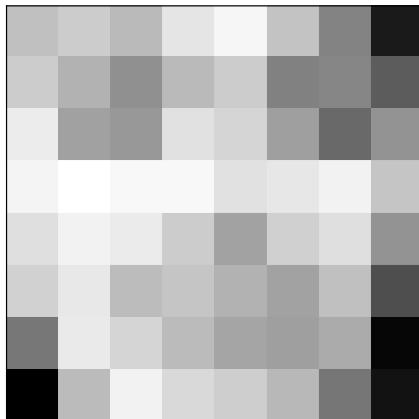
DFT then only involves cosines

Very important in image processing: **low-frequency** DCT components contain most of the energy in natural images

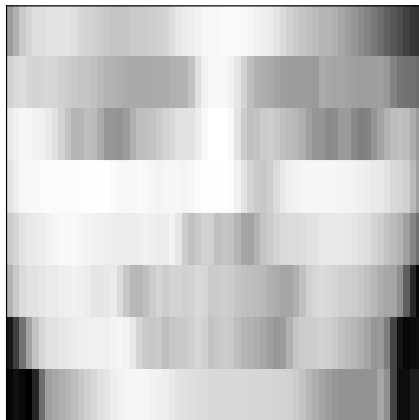
Average magnitudes of each 2D DCT coefficient in a database of patches



Projection of 8×8 patches onto first DCT basis vector



Projection of 8×8 patches onto first 5 DCT basis vectors



Projection of 8×8 patches onto first 15 DCT basis vectors



Projection of 8×8 patches onto first 30 DCT basis vectors



Projection of 8×8 patches onto first 50 DCT basis vectors



Original image



Quantizing the low frequencies



Quantizing the high frequencies



JPEG algorithm

1. Choose a quality setting $Q \in (0, 100)$
2. Divide image into 8×8 pixel patches
3. Compute the 2D DCT of each patch
4. Let $\hat{P} \in \mathbb{R}^{8 \times 8}$ denote the 2D DCT of a patch. Set

$$\hat{P}'_{ij} = \text{round} \left(\frac{\hat{P}_{ij}}{S(Q)M_{ij}} \right) S(Q)M_{ij}, \quad (1)$$

where $S(Q)$ is the quality scaling factor:

$$S(Q) := \begin{cases} \frac{100-Q}{50} & \text{if } Q > 50 \\ \frac{50}{Q} & \text{otherwise} \end{cases} \quad (2)$$

5. Compute the inverse 2D DCT of each quantized patch \hat{P}' and encode

JPEG DCT Quantization Matrix

$$M = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

JPEG



Fourier Representations

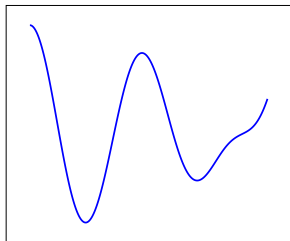
Sampling theorem

Convolution

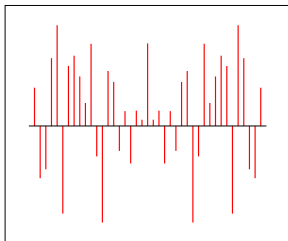
Wiener deconvolution

Sampling a bandlimited signal

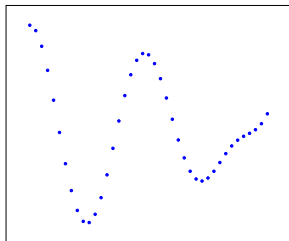
Signal



Spectrum



Samples



Important questions

1. What sampling rate is necessary to preserve all the information?
2. How can we reconstruct the signal from the samples?

Nyquist-Shannon-Kotelnikov sampling theorem

Any bandlimited signal $g \in \mathcal{L}_2 [0, 1]$ of the form

$$g(t) := \sum_{k=-k_c}^{k_c} G[k] h_k(t)$$

can be recovered from n samples $g(0), g(1/n), \dots, g((n-1)/n)$ as long as

the sampling rate $f_s := n$ satisfies

$$f_s \geq 2k_c + 1$$

which is known as the **Nyquist rate**

Proof

$$\vec{g}_n := \begin{bmatrix} g(0) \\ g\left(\frac{1}{n}\right) \\ \dots \\ g\left(\frac{n-1}{n}\right) \end{bmatrix} = \begin{bmatrix} \sum_{k=-k_c}^{k_c} G[k] h_k(0) \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{1}{n}\right) \\ \dots \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{n-1}{n}\right) \end{bmatrix}$$

Proof

$$\begin{aligned}\vec{g}_n &:= \begin{bmatrix} g(0) \\ g\left(\frac{1}{n}\right) \\ \dots \\ g\left(\frac{n-1}{n}\right) \end{bmatrix} = \begin{bmatrix} \sum_{k=-k_c}^{k_c} G[k] h_k(0) \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{1}{n}\right) \\ \dots \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{n-1}{n}\right) \end{bmatrix} \\ &= \sum_{k=-k_c}^{k_c} G[k] \begin{bmatrix} h_k\left(\frac{1}{n}\right) \\ h_k\left(\frac{2}{n}\right) \\ \dots \\ h_k(1) \end{bmatrix} = \sum_{k=-k_c}^{k_c} G[k] \vec{h}_k^{[n]}\end{aligned}$$

Proof

$$\begin{aligned}\vec{g}_n &= \begin{bmatrix} \vec{h}_{-k_s}^{[n]} & \vec{h}_{-k_s+1}^{[n]} & \cdots & \vec{h}_{k_s}^{[n]} \end{bmatrix} \vec{G} \\ &= F \vec{G}\end{aligned}$$

$$\vec{G}[k] := \begin{cases} G[k], & \text{if } |k| \leq k_c \\ 0, & \text{otherwise} \end{cases}$$

F is a square matrix with **orthogonal** columns

Dirichlet-kernel interpolation

Any bandlimited signal $g \in \mathcal{L}_2 [0, 1]$ of the form

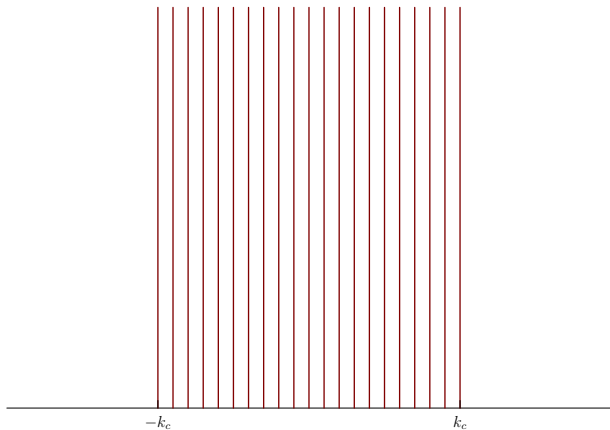
$$g(t) := \sum_{k=-k_c}^{k_c} G[k] h_k(t)$$

satisfies

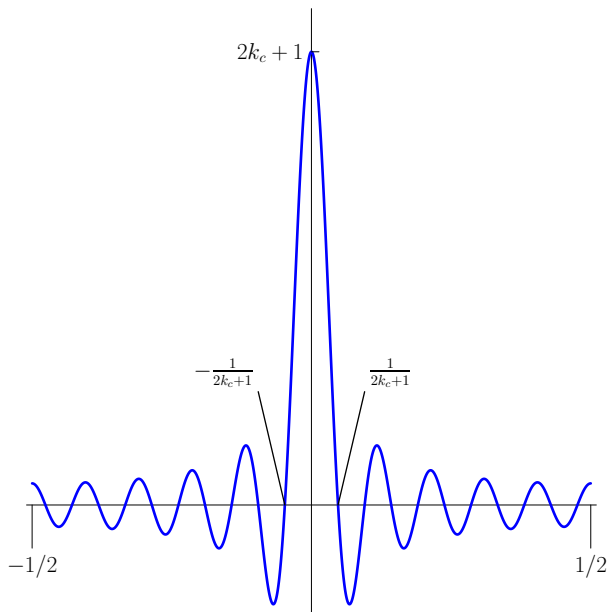
$$g(t) = \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) d(t - j/n)$$

where d is a Dirichlet kernel with cut-off frequency k_c

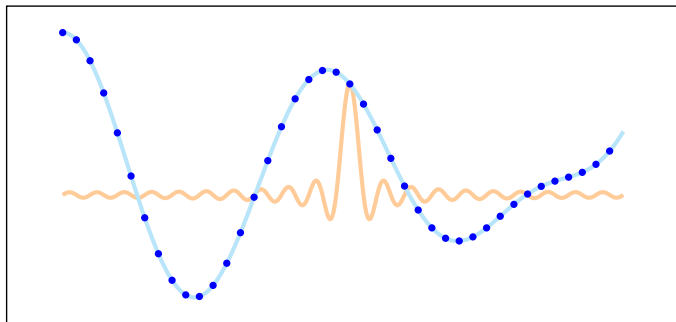
Dirichlet kernel (spectrum)



Dirichlet kernel



Dirichlet-kernel interpolation



Proof

$$\vec{a}_t := [\exp(-2\pi k_s t) \quad \exp(-2\pi(k_s - 1)t) \quad \cdots \quad \exp(2\pi k_s t)]^T$$

$$F^* = [\vec{a}_0 \quad \vec{a}_{1/n} \quad \cdots \quad \vec{a}_{(n-1)/n}]$$

Proof

$$\vec{a}_t := [\exp(-2\pi k_s t) \quad \exp(-2\pi(k_s - 1)t) \quad \cdots \quad \exp(2\pi k_s t)]^T$$

$$F^* = [\vec{a}_0 \quad \vec{a}_{1/n} \quad \cdots \quad \vec{a}_{(n-1)/n}]$$

$$\vec{G} = F^* \vec{g}_n = \frac{1}{n} \sum_{j=1}^n g(j/n) \vec{a}_{j/n}$$

Proof

$$g(t) = \frac{1}{n} \sum_{k=-k_c}^{k_c} G[k] e^{-i2\pi kt} = \frac{1}{n} \vec{a}_t^* \vec{G}$$

Proof

$$g(t) = \frac{1}{n} \sum_{k=-k_c}^{k_c} G[k] e^{-i2\pi kt} = \frac{1}{n} \vec{a}_t^* \vec{G}$$

$$d(t - \tau) = \sum_{k=-k_c}^{k_c} e^{-i2\pi k(t-\tau)} = \vec{a}_t^* \vec{a}_\tau$$

Proof

$$\vec{G} = \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) \vec{a}_{j/n} \quad g(t) = \frac{1}{n} \vec{a}_t^* \vec{G} \quad d(t - \tau) = \vec{a}_t^* \vec{a}_\tau$$

$$g(t) = \frac{1}{n} \vec{a}_t^* \vec{G}$$

Proof

$$\vec{G} = \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) \vec{a}_{j/n} \quad g(t) = \frac{1}{n} \vec{a}_t^* \vec{G} \quad d(t - \tau) = \vec{a}_t^* \vec{a}_\tau$$

$$\begin{aligned} g(t) &= \frac{1}{n} \vec{a}_t^* \vec{G} \\ &= \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) \vec{a}_t^* \vec{a}_{j/n} \end{aligned}$$

Proof

$$\vec{G} = \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) \vec{a}_{j/n} \quad g(t) = \frac{1}{n} \vec{a}_t^* \vec{G} \quad d(t - \tau) = \vec{a}_t^* \vec{a}_\tau$$

$$\begin{aligned} g(t) &= \frac{1}{n} \vec{a}_t^* \vec{G} \\ &= \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) \vec{a}_t^* \vec{a}_{j/n} \\ &= \frac{1}{n} \sum_{j=0}^{n-1} g(j/n) d(t - j/n) \end{aligned}$$

Aliasing

We sample

$$g(t) := \sum_{k=-k_c}^{k_c+1} G[k] h_k(t)$$

at a rate $k_s := k_c/2$ (instead of $k_c + 1$), so $n := 2k_s + 1 = k_c + 1$

Aliasing

$$\begin{aligned}\vec{g}_n &:= \begin{bmatrix} g(0) \\ g\left(\frac{1}{n}\right) \\ \dots \\ g\left(\frac{n-1}{n}\right) \end{bmatrix} = \begin{bmatrix} \sum_{k=-k_c}^{k_c} G[k] h_k(0) \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{1}{n}\right) \\ \dots \\ \sum_{k=-k_c}^{k_c} G[k] h_k\left(\frac{n-1}{n}\right) \end{bmatrix} \\ &= \sum_{k=-k_c}^{k_c} G[k] \begin{bmatrix} h_k(0) \\ h_k\left(\frac{1}{n}\right) \\ \dots \\ h_k\left(\frac{n-1}{n}\right) \end{bmatrix} = \sum_{k=-k_c}^{k_c} G[k] \vec{h}_k^{[n]}\end{aligned}$$

Aliasing

For any k , $\vec{h}_k^{[n]} = \vec{h}_{k+n}^{[n]}$

$$\begin{aligned}\vec{g}_n &= \begin{bmatrix} \vec{h}_{-k_c}^{[n]} & \cdots & \vec{h}_0^{[n]} & \vec{h}_1^{[n]} & \cdots & \vec{h}_{k_c+1}^{[n]} \end{bmatrix} \vec{G} \\ &= \begin{bmatrix} \vec{h}_{-2k_s}^{[n]} & \cdots & \vec{h}_0^{[n]} & \vec{h}_1^{[n]} & \cdots & \vec{h}_{2k_s+1}^{[n]} \end{bmatrix} \vec{G}\end{aligned}$$

\tilde{F} is a square matrix with **orthogonal** columns

Aliasing

For any k , $\vec{h}_k^{[n]} = \vec{h}_{k+n}^{[n]}$

$$\begin{aligned}\vec{g}_n &= \begin{bmatrix} \vec{h}_{-k_c}^{[n]} & \dots & \vec{h}_0^{[n]} & \vec{h}_1^{[n]} & \dots & \vec{h}_{k_c+1}^{[n]} \end{bmatrix} \vec{G} \\ &= \begin{bmatrix} \vec{h}_{-2k_s}^{[n]} & \dots & \vec{h}_0^{[n]} & \vec{h}_1^{[n]} & \dots & \vec{h}_{2k_s+1}^{[n]} \end{bmatrix} \vec{G} \\ &= \begin{bmatrix} \vec{h}_1^{[n]} & \dots & \vec{h}_n^{[n]} & \vec{h}_1^{[n]} & \dots & \vec{h}_n^{[n]} \end{bmatrix} \vec{G} \\ &= \begin{bmatrix} \tilde{F} & \tilde{F} \end{bmatrix} \begin{bmatrix} \vec{G}_1 \\ \vec{G}_2 \end{bmatrix}\end{aligned}$$

\tilde{F} is a square matrix with **orthogonal** columns

Aliasing

If $n = 2k_c + 1$

$$\vec{G} = \frac{1}{n} \tilde{F}^* \vec{g}_n$$

Aliasing

If $n = 2k_c + 1$

$$\vec{G} = \frac{1}{n} \tilde{F}^* \vec{g}_n$$

In this case

$$\begin{aligned} \vec{G}_{\text{aliased}} &= \frac{1}{n} \tilde{F}^* \vec{g}_n \\ &= \frac{1}{n} \tilde{F}^* \begin{bmatrix} \tilde{F} & \tilde{F} \end{bmatrix} \begin{bmatrix} \vec{G}_1 \\ \vec{G}_2 \end{bmatrix} \end{aligned}$$

Aliasing

If $n = 2k_c + 1$

$$\vec{G} = \frac{1}{n} \tilde{F}^* \vec{g}_n$$

In this case

$$\begin{aligned} \vec{G}_{\text{aliased}} &= \frac{1}{n} \tilde{F}^* \vec{g}_n \\ &= \frac{1}{n} \tilde{F}^* \begin{bmatrix} \tilde{F} & \tilde{F} \end{bmatrix} \begin{bmatrix} \vec{G}_1 \\ \vec{G}_2 \end{bmatrix} \\ &= \vec{G}_1 + \vec{G}_2 \end{aligned}$$

Fourier Representations

Sampling theorem

Convolution

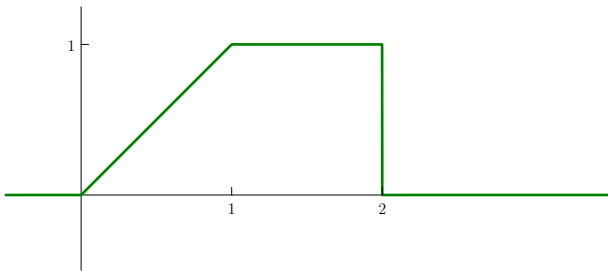
Wiener deconvolution

Convolution

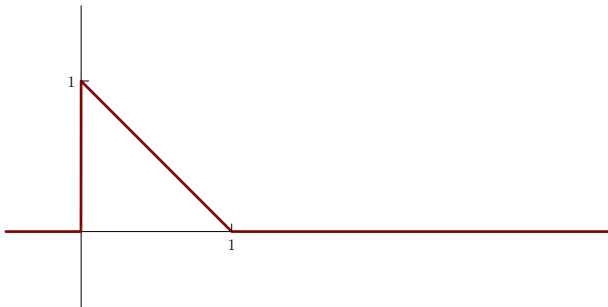
The convolution of two functions $f, g \in \mathcal{L}_2[-1/2, 1/2]$ is defined as

$$f * g(t) := \int_{-1/2}^{1/2} f(u) g(t-u) du$$

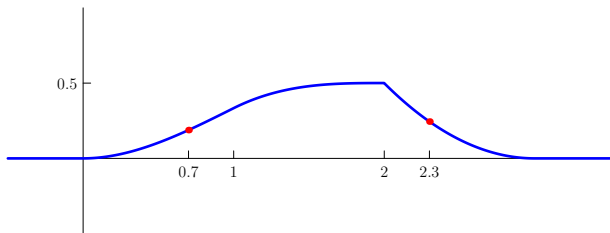
f



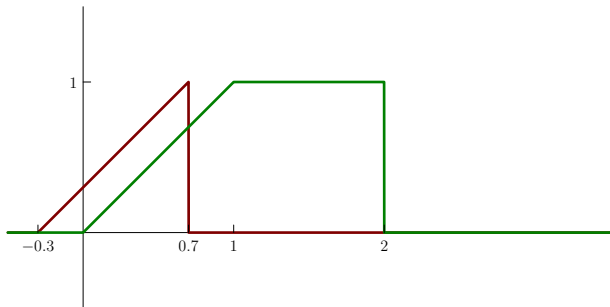
σ



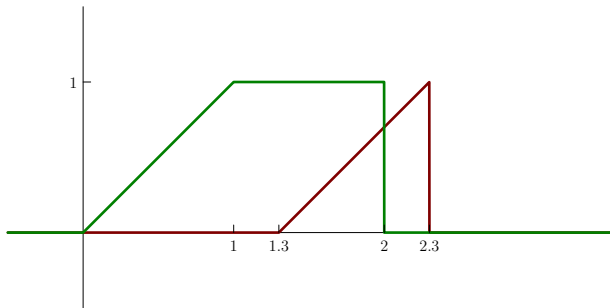
$f * g$



$$f(t)g(0.7 - t)$$



$$f(t)g(2.3 - t)$$



Time shift

The τ -shifted version of a function $f \in \mathcal{L}_2[-1/2, 1/2]$ is

$$f_{[\tau]}(t) := f(t - \tau)$$

where the shift is *circular* (it wraps around)

For any shift τ

$$F_{[\tau]}[k] = \exp(-i2\pi k\tau) F[k]$$

Proof

We interpret f as a periodic function such that $f(t + 1) = f(t)$

$$F_{[\tau]}[k] = \int_{-1/2}^{1/2} f(t - \tau) \exp(-i2\pi kt) dt$$

Proof

We interpret f as a periodic function such that $f(t + 1) = f(t)$

$$\begin{aligned} F_{[\tau]}[k] &= \int_{-1/2}^{1/2} f(t - \tau) \exp(-i2\pi kt) dt \\ &= \int_{-1/2-\tau}^{1/2-\tau} f(u) \exp(-i2\pi k(u + \tau)) dt \end{aligned}$$

Proof

We interpret f as a periodic function such that $f(t + 1) = f(t)$

$$\begin{aligned} F_{[\tau]}[k] &= \int_{-1/2}^{1/2} f(t - \tau) \exp(-i2\pi kt) dt \\ &= \int_{-1/2-\tau}^{1/2-\tau} f(u) \exp(-i2\pi k(u + \tau)) dt \\ &= \exp(-i2\pi k\tau) F[k] \end{aligned}$$

Convolution in time is multiplication in frequency

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$R[k] = F[k] G[k]$$

We can compute convolutions **very fast** using the FFT

Proof

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$R[k] := \int_{-1/2}^{1/2} \exp(-i2\pi kt) f * g(t) dt$$

Proof

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$\begin{aligned} R[k] &:= \int_{-1/2}^{1/2} \exp(-i2\pi kt) f * g(t) dt \\ &= \int_{-1/2}^{1/2} \exp(-i2\pi kt) \int_{-1/2}^{1/2} f(u) g(t-u) du dt \end{aligned}$$

Proof

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$\begin{aligned} R[k] &:= \int_{-1/2}^{1/2} \exp(-i2\pi kt) f * g(t) dt \\ &= \int_{-1/2}^{1/2} \exp(-i2\pi kt) \int_{-1/2}^{1/2} f(u) g(t-u) du dt \\ &= \int_{-1/2}^{1/2} f(u) \int_{-1/2}^{1/2} \exp(-i2\pi kt) g(t-u) dt du \end{aligned}$$

Proof

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$\begin{aligned} R[k] &:= \int_{-1/2}^{1/2} \exp(-i2\pi kt) f * g(t) dt \\ &= \int_{-1/2}^{1/2} \exp(-i2\pi kt) \int_{-1/2}^{1/2} f(u) g(t-u) du dt \\ &= \int_{-1/2}^{1/2} f(u) \int_{-1/2}^{1/2} \exp(-i2\pi kt) g(t-u) dt du \\ &= \int_{-1/2}^{1/2} f(u) G[k] \exp(-i2\pi ku) dt du \end{aligned}$$

Proof

Let $r := f * g$ for $f, g \in \mathcal{L}_2[-1/2, 1/2]$. Then

$$\begin{aligned} R[k] &:= \int_{-1/2}^{1/2} \exp(-i2\pi kt) f * g(t) dt \\ &= \int_{-1/2}^{1/2} \exp(-i2\pi kt) \int_{-1/2}^{1/2} f(u) g(t-u) du dt \\ &= \int_{-1/2}^{1/2} f(u) \int_{-1/2}^{1/2} \exp(-i2\pi kt) g(t-u) dt du \\ &= \int_{-1/2}^{1/2} f(u) G[k] \exp(-i2\pi ku) dt du \\ &= F[k] G[k] \end{aligned}$$

Central limit theorem

Let x_1, x_2, x_3, \dots be a sequence of iid random variables with mean μ and bounded variance σ^2

The sequence of averages a_1, a_2, a_3, \dots is defined as

$$\mathbf{a}_i := \frac{1}{i} \sum_{j=1}^i \mathbf{x}_j$$

Central limit theorem

The sequence $\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3, \dots$

$$\mathbf{b}_i := \sqrt{i}(\mathbf{a}_i - \mu)$$

converges in distribution to a Gaussian random variable with mean 0 and variance σ^2

For any $x \in \mathbb{R}$

$$\lim_{i \rightarrow \infty} f_{\mathbf{b}_i}(x) := \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

For large i the theorem suggests that the average \mathbf{a}_i is approximately **Gaussian** with mean μ and variance σ/\sqrt{n}

Sum of independent random variables

If x and y are independent random variables, the pdf of

$$z = x + y$$

is equal to the **convolution** of f_x and f_y

$$f_z(z) = \int_{u=-\infty}^{\infty} f_x(z-u) f_y(u) du$$

Proof

$$F_z(z)$$

Proof

$$F_z(z) = P(\mathbf{x} + \mathbf{y} \leq z)$$

Proof

$$\begin{aligned} F_z(z) &= P(\mathbf{x} + \mathbf{y} \leq z) \\ &= \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{z-y} f_{\mathbf{x},\mathbf{y}}(x, y) dx dy \end{aligned}$$

Proof

$$\begin{aligned} F_z(z) &= P(\mathbf{x} + \mathbf{y} \leq z) \\ &= \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{z-y} f_{\mathbf{x},\mathbf{y}}(x, y) dx dy \\ &= \int_{y=-\infty}^{\infty} \int_{u=-\infty}^z f_{\mathbf{x},\mathbf{y}}(u - y, y) du dy \quad (u = x + y) \end{aligned}$$

Proof

$$\begin{aligned}F_z(z) &= P(\mathbf{x} + \mathbf{y} \leq z) \\&= \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{z-y} f_{\mathbf{x},\mathbf{y}}(x, y) dx dy \\&= \int_{y=-\infty}^{\infty} \int_{u=-\infty}^z f_{\mathbf{x},\mathbf{y}}(u - y, y) du dy \quad (u = x + y) \\&= \int_{u=-\infty}^z \int_{y=-\infty}^{\infty} f_{\mathbf{x},\mathbf{y}}(u - y, y) dy du\end{aligned}$$

Proof

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$$f_z(z) = \int_{y=-\infty}^{\infty} f_{\mathbf{x},\mathbf{y}}(z - y, y) dy$$

Proof

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$$\begin{aligned}f_z(z) &= \int_{y=-\infty}^{\infty} f_{\mathbf{x},\mathbf{y}}(z - y, y) dy \\&= \int_{y=-\infty}^{\infty} f_x(z - y) f_y(y) dy\end{aligned}$$

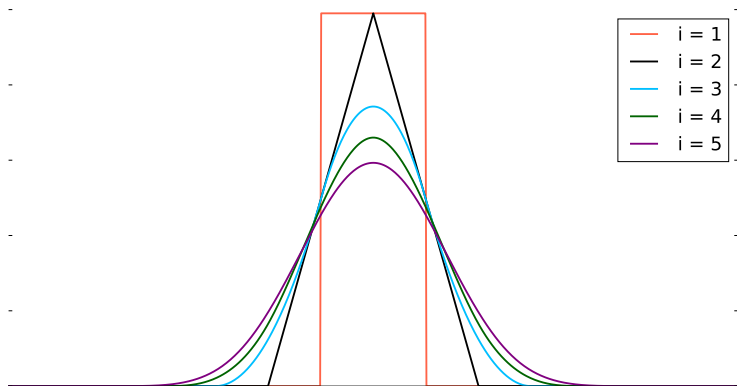
Sketch of proof of central limit theorem

Sequence of iid random variables x_1, x_2, x_3, \dots with pdf f

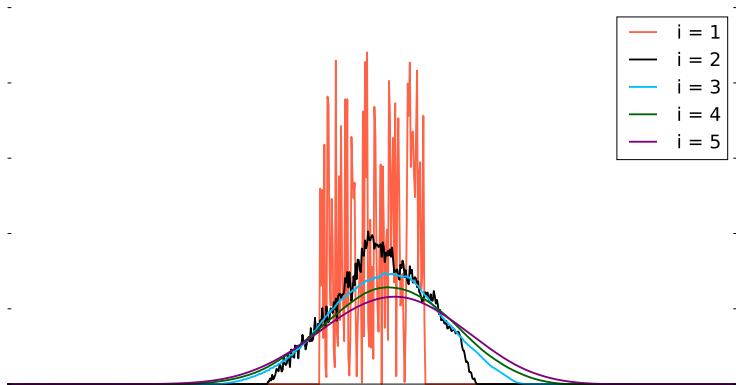
The pdf of the sum is given by

$$f_{\sum_{j=1}^{\infty} x_j}(x) = (f * f * \dots)(x)$$

Sketch of proof of central limit theorem



Sketch of proof of central limit theorem



Discrete convolution

The circular convolution of $\vec{x}, \vec{y} \in \mathbb{C}^n$ is

$$\vec{x} * \vec{y}[j] := \sum_{m=0}^{n-1} \vec{x}[m] \vec{y}[j - m], \quad 0 \leq j \leq n - 1$$

where the shifts are **circular**, so that $\vec{x}[j] = \vec{x}[j + n]$ and $\vec{y}[j] = \vec{y}[j + n]$

Convolution matrix

$$C_{\vec{y}} := \begin{bmatrix} \vec{y}[0] & \vec{y}[n-1] & \cdots & \vec{y}[2] & \vec{y}[1] \\ \vec{y}[1] & \vec{y}[0] & \cdots & \vec{y}[3] & \vec{y}[2] \\ & & \cdots & & \\ \vec{y}[n-1] & \vec{y}[n-2] & \cdots & \vec{y}[1] & \vec{y}[0] \end{bmatrix}$$

Matrices with this structure are called **circulant** matrices

Assuming entries are numbered from 0 to $n-1$, for any $\vec{x} \in \mathbb{C}^n$

$$\vec{x} * \vec{y} = C_{\vec{y}} \vec{x}$$

Convolution in time is multiplication in frequency

Let $\vec{r} := \vec{x} * \vec{y}$ for $\vec{x}, \vec{y} \in \mathbb{C}^n$. Then

$$\vec{R}[k] = \vec{X}[k] \vec{Y}[k]$$

Discrete time shift

The m -shifted version of $\vec{x} \in \mathbb{C}^n$ is

$$\vec{x}_{[m]}[j] := \vec{x}(j - m)$$

where the shift is *circular*, so $\vec{x}(j + n) = \vec{x}(j)$

For any shift m we have

$$\vec{X}_{[m]}[k] = \exp(-i2\pi km) \vec{X}[k]$$

Proof

$$\vec{X}_{[m]}[k] = \sum_{j=0}^{n-1} \vec{x}_{[\tau]}[j] \exp(-2\pi kj)$$

Proof

$$\begin{aligned}\vec{X}_{[m]}[k] &= \sum_{j=0}^{n-1} \vec{x}_{[\tau]}[j] \exp(-2\pi k j) \\ &= \sum_{l=-m}^{n-1-m} \vec{x}[l] \exp(-2\pi k (l + m))\end{aligned}$$

Proof

$$\begin{aligned}\vec{X}_{[m]}[k] &= \sum_{j=0}^{n-1} \vec{x}_{[\tau]}[j] \exp(-2\pi k j) \\ &= \sum_{l=-m}^{n-1-m} \vec{x}[l] \exp(-2\pi k (l + m)) \\ &= \exp(-i2\pi km) \vec{X}[k]\end{aligned}$$

Convolution in time is multiplication in frequency

$$R[k] := \sum_{j=0}^{n-1} \exp(-i2\pi kj) \sum_{m=0}^{n-1} \vec{x}[m] \vec{y}[j-m]$$

Convolution in time is multiplication in frequency

$$\begin{aligned} R[k] &:= \sum_{j=0}^{n-1} \exp(-i2\pi kj) \sum_{m=0}^{n-1} \vec{x}[m] \vec{y}[j-m] \\ &= \sum_{m=0}^{n-1} \vec{x}[m] \sum_{j=0}^{n-1} \exp(-i2\pi kj) \vec{y}[j-m] \end{aligned}$$

Convolution in time is multiplication in frequency

$$\begin{aligned}R[k] &:= \sum_{j=0}^{n-1} \exp(-i2\pi kj) \sum_{m=0}^{n-1} \vec{x}[m] \vec{y}[j-m] \\&= \sum_{m=0}^{n-1} \vec{x}[m] \sum_{j=0}^{n-1} \exp(-i2\pi kj) \vec{y}[j-m] \\&= \sum_{m=0}^{n-1} \vec{x}[m] \exp(-i2\pi km) \vec{Y}[k]\end{aligned}$$

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$$\begin{aligned}R[k] &:= \sum_{j=0}^{n-1} \exp(-i2\pi kj) \sum_{m=0}^{n-1} \vec{x}[m] \vec{y}[j-m] \\&= \sum_{m=0}^{n-1} \vec{x}[m] \sum_{j=0}^{n-1} \exp(-i2\pi kj) \vec{y}[j-m] \\&= \sum_{m=0}^{n-1} \vec{x}[m] \exp(-i2\pi km) \vec{Y}[k] \\&= \vec{X}[k] \vec{Y}[k]\end{aligned}$$

Eigendecomposition of circulant matrices

For any vector $\vec{x} \in \mathbb{C}^n$

$$\begin{aligned}C_{\vec{y}} &= \vec{x} * \vec{y} \\&= \frac{1}{n} W^* \Lambda_{\vec{y}} W \vec{x} \\&= \frac{1}{n} W^* \Lambda_{\vec{y}} W \vec{x}.\end{aligned}$$

Eigendecomposition of circulant matrices

For any vector $\vec{x} \in \mathbb{C}^n$

$$\begin{aligned}C_{\vec{y}} &= \vec{x} * \vec{y} \\&= \frac{1}{n} W^* \Lambda_{\vec{y}} \vec{X} \\&= \frac{1}{n} W^* \Lambda_{\vec{y}} W \vec{x}.\end{aligned}$$

For any circulant matrix $C_{\vec{y}}$ corresponding to a vector \vec{y}

$$C_{\vec{y}} = \frac{1}{n} W^* \Lambda_{\vec{y}} W$$

Fourier Representations

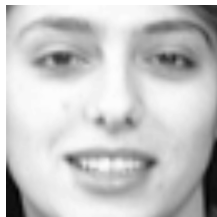
Sampling theorem

Convolution

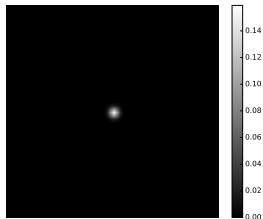
Wiener deconvolution

Noiseless data

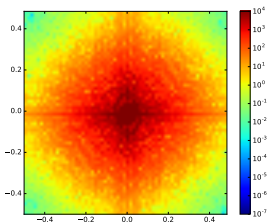
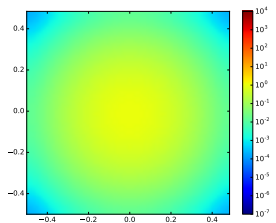
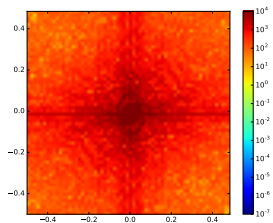
X



K



B

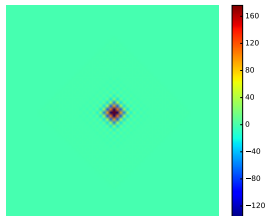


Deconvolution

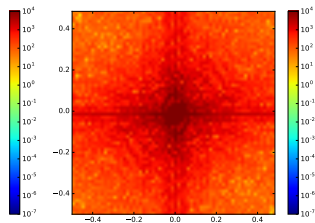
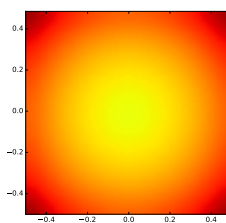
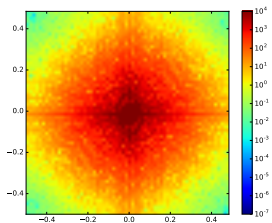
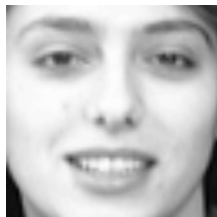
B



K_{dec}



X_{est}



Noisy data

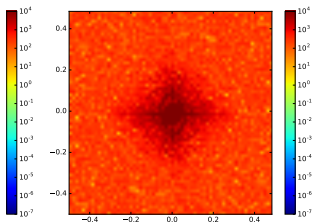
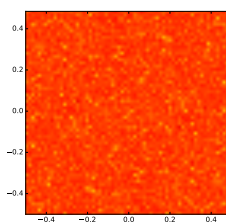
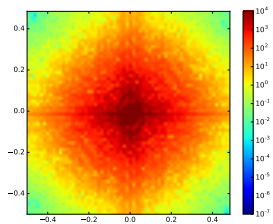
B



Z



B_{noisy}

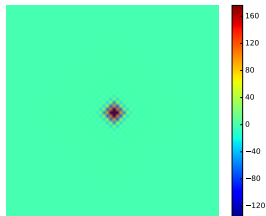


Naive deconvolution

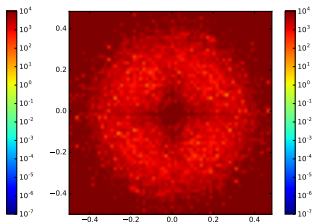
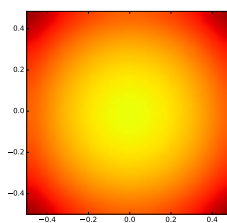
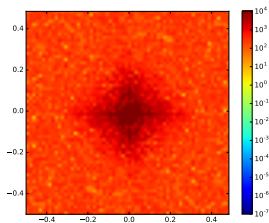
B_{noisy}



K_{dec}



X_{naive}



Vector space of zero-mean random variables

Zero-mean complex-valued random variables form a vector space

The **covariance** is a valid inner product

The **variance** is the inner-product norm

By Chebyshev's inequality if $\|\mathbf{x}\|_{\langle \cdot, \cdot \rangle} = 0$, for any $\epsilon > 0$

$$P(|\mathbf{x}| > \epsilon) \leq$$

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The **covariance** is a valid inner product

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By Chebyshev's inequality if $\|\mathbf{x}\|_{\langle \cdot, \cdot \rangle} = 0$, for any $\epsilon > 0$

$$P(|\mathbf{x}| > \epsilon) \leq \frac{\text{Var}(\mathbf{x})}{\epsilon^2} = 0$$

so \mathbf{x} with probability one

Linear estimation

Let

$$\mathbf{y} = \mathbf{a}\mathbf{x} + \mathbf{z}$$

what is the linear estimate

$$\mathbf{x}_{\text{MMSE}} := \mathbf{w}\mathbf{y}$$

that minimizes

$$E\left((\mathbf{x} - \mathbf{x}_{\text{MMSE}})^2\right)$$

Linear estimation

We want a vector in the span of \mathbf{y} that minimizes

$$E \left((\mathbf{x} - \mathbf{x}_{\text{MMSE}})^2 \right) = \|\mathbf{x} - \mathbf{x}_{\text{MMSE}}\|_{\langle \cdot, \cdot \rangle}^2$$

Projection

$$\mathcal{P}_{\text{span}(\mathbf{y})} \mathbf{x} = \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}}$$

Projection

$$w = \frac{1}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle$$

Projection

$$\begin{aligned} w &= \frac{1}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle \\ &= \frac{\langle \mathbf{x}, a\mathbf{x} + \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \end{aligned}$$

Projection

$$\begin{aligned}w &= \frac{1}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle \\&= \frac{\langle \mathbf{x}, a\mathbf{x} + \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a \|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}^2 + a \langle \mathbf{x}, \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2}\end{aligned}$$

Projection

$$\begin{aligned}w &= \frac{1}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle \\&= \frac{\langle \mathbf{x}, a\mathbf{x} + \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a \|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}^2 + a \langle \mathbf{x}, \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a \|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}}{a^2 \|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}^2 + \|\mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2}\end{aligned}$$

Projection

$$\begin{aligned}w &= \frac{1}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \left\langle \mathbf{x}, \frac{\mathbf{y}}{\|\mathbf{y}\|_{\langle \cdot, \cdot \rangle}} \right\rangle \\&= \frac{\langle \mathbf{x}, a\mathbf{x} + \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a\|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}^2 + a\langle \mathbf{x}, \mathbf{z} \rangle}{\|a\mathbf{x} + \mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a\|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}}{a^2\|\mathbf{x}\|_{\langle \cdot, \cdot \rangle}^2 + \|\mathbf{z}\|_{\langle \cdot, \cdot \rangle}^2} \\&= \frac{a\sigma_{\mathbf{x}}}{a^2\sigma_{\mathbf{x}}^2 + \sigma_{\mathbf{z}}^2}\end{aligned}$$

Wiener deconvolution

Given $B_{\text{noisy}} \in \mathbb{R}^{n \times n}$ and a kernel $K \in \mathbb{R}^{n \times n}$

1. Estimate variance of each 2D DFT coefficient $\sigma_Z [k_1, k_2]$.

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3. Compute \hat{B}_{noisy} and \hat{K}
4. For $0 \leq k_1, k_2 \leq n - 1$

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3. Compute \hat{B}_{noisy} and \hat{K}
4. For $0 \leq k_1, k_2 \leq n - 1$
 - ▶ Center $\hat{B}_{\text{noisy}}[k_1, k_2]$ by subtracting $\hat{K}[k_1, k_2]\mu_X [k_1, k_2]$ to obtain \hat{B}_c

Wiener deconvolution

Given $B_{\text{noisy}} \in \mathbb{R}^{n \times n}$ and a kernel $K \in \mathbb{R}^{n \times n}$

1. Estimate variance of each 2D DFT coefficient $\sigma_Z [k_1, k_2]$.
2. Estimate mean $\mu_X [k_1, k_2]$ and variance $\sigma_X [k_1, k_2]$ of each 2D DFT coefficient $\hat{X} [k_1, k_2]$
3. Compute \hat{B}_{noisy} and \hat{K}
4. For $0 \leq k_1, k_2 \leq n - 1$
 - ▶ Center $\hat{B}_{\text{noisy}} [k_1, k_2]$ by subtracting $\hat{K} [k_1, k_2] \mu_X [k_1, k_2]$ to obtain \hat{B}_c
 - ▶ Set

$$W[k_1, k_2] := \frac{\hat{K}[k_1, k_2] \sigma_X [k_1, k_2]}{\hat{K}[k_1, k_2]^2 \sigma_X [k_1, k_2]^2 + \sigma_Z [k_1, k_2]^2}$$

$$X_W := \mu_X [k_1, k_2] + W[k_1, k_2] \hat{B}_c [k_1, k_2]$$

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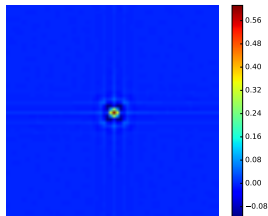
5. Compute the inverse 2D DFT of X_W .

Wiener deconvolution

B_{noisy}



W



X_W

