

Fast Multidimensional Signal Processing with Shearlab.jl

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(github: **arsenal9971**)

Notebook and Beamer:

<https://github.com/arsenal997/Shearlab.jl/presentations/JuliaCon2017>

TU Berlin, BMS

22th of June, 2017



images/tub'afg.jpg

What is a signal?

Our definition

Function (or something that can be represented as) that contains information about the behavior or attributes of some phenomenon. It can be digital (discrete) or analog (continuous).

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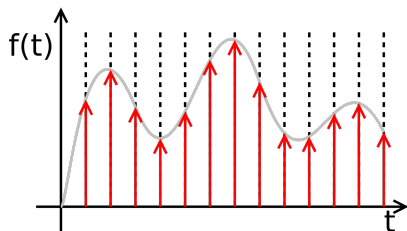


Figure: Digital and continuous one-dimensional signals

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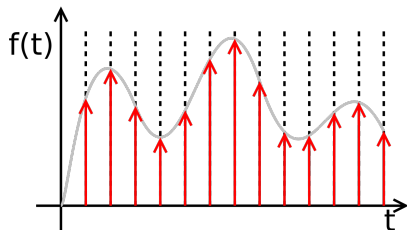


Figure: Digital and continuous one-dimensional signals

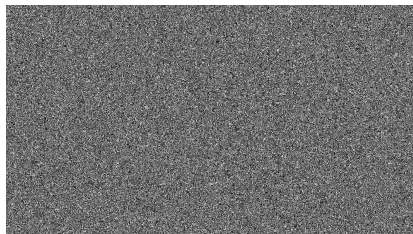


Figure: White noise, not a signal

Sparse representations of signals

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- ▶ Goal: Find the right dictionary to represent optimally our data.

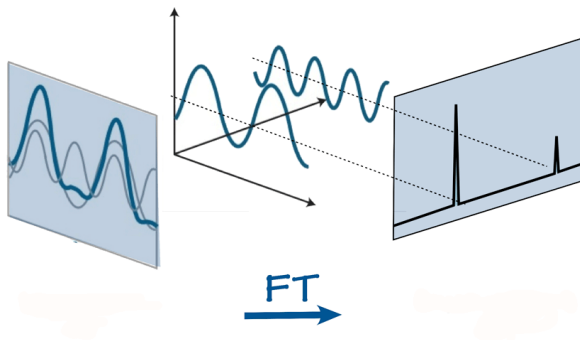
The diagram illustrates the equation $x = D \hat{\alpha}$. On the left, a vertical blue bar represents the signal x . This is equal to a matrix multiplication. The matrix is the Sparse Dictionary D , which is composed of several columns of different colors (red, blue, yellow, and green) and vertical ellipses indicating more columns. To the right of the matrix is a vertical vector of Sparse Coefficients $\hat{\alpha}$. This vector consists of several small boxes, some of which are highlighted with colored borders (red, blue, yellow, and green) to show that only a few coefficients are non-zero, representing sparsity.

Fourier Transform (Fourier, 1822)

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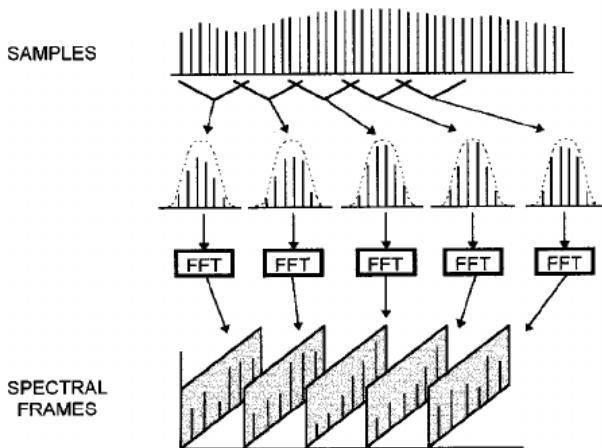


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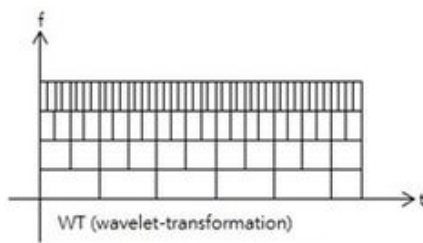
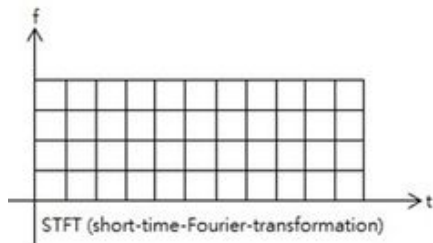
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Cartoon-like functions

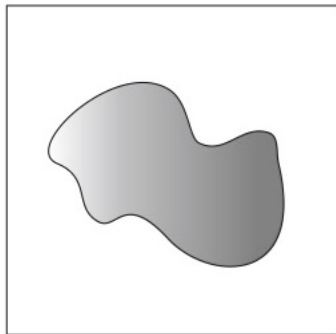
Definition

Let $f : \mathbb{R}^2 \rightarrow \mathbb{C}$, $f \in \mathcal{E}^2(\mathbb{R}^2)$ if $f = f_0 + \chi_B f_1$, with $B \subset [0, 1]^2$, $\partial B \in C^2$ and with bounded curvature. Moreover, $f_i \in C^2(\mathbb{R}^2)$ with $\|f_i\|_{C^2} \leq 1$ and $\text{supp} f_i \subset [0, 1]^2$ for $i = 0, 1$.

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Optimal error for 2D signals

Best N-term approx. error (Donoho, 2001)

Let $\{\psi_\lambda\}_{\lambda \in \Lambda} \subset L^2(\mathbb{R}^2)$ a frame. The optimal best N-Term approximation error for any $f \in \mathcal{R}^2(\mathbb{R}^2)$ is

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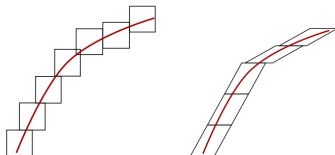
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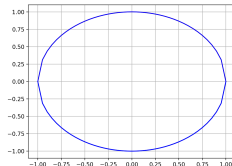
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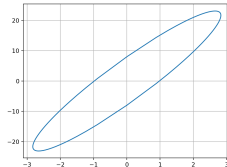
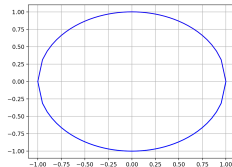
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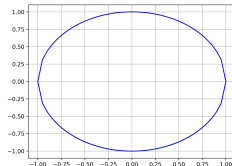
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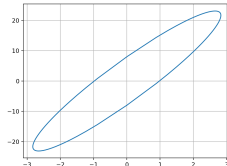
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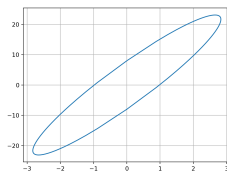
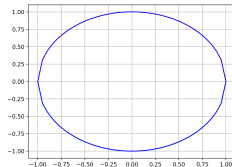
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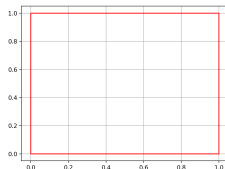
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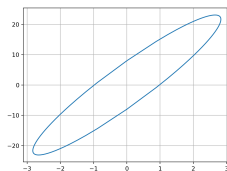
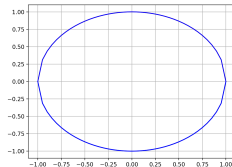
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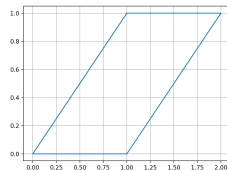
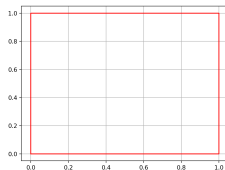
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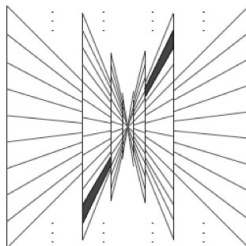
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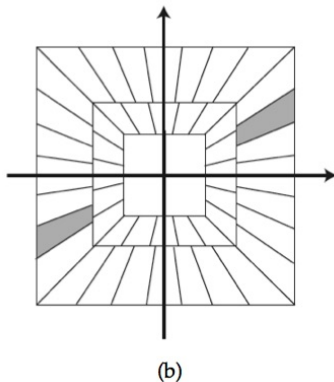
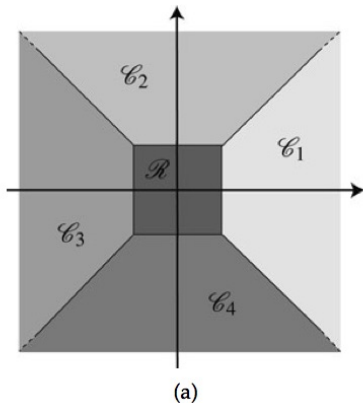


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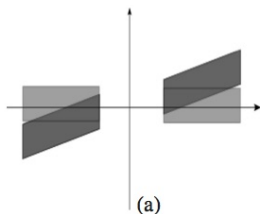
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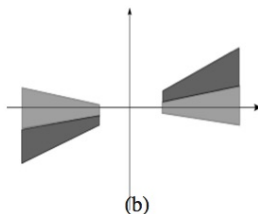
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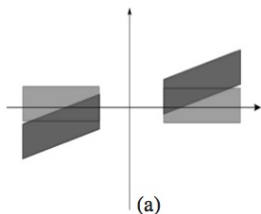
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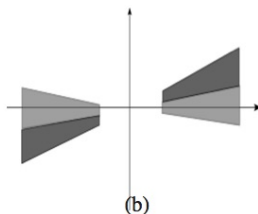
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► Best N -term approximation error

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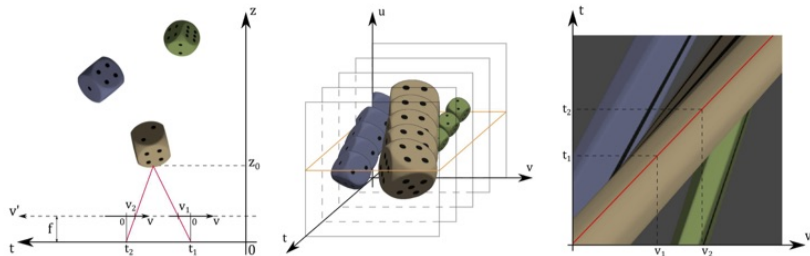
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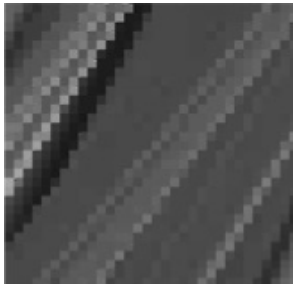
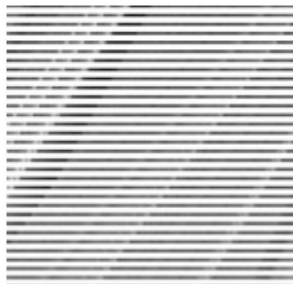
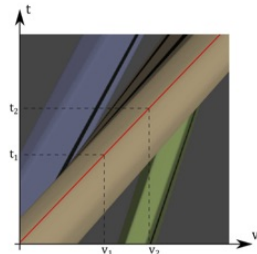
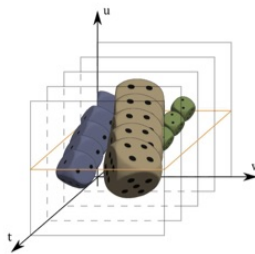
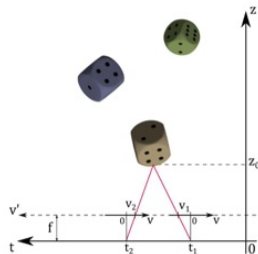
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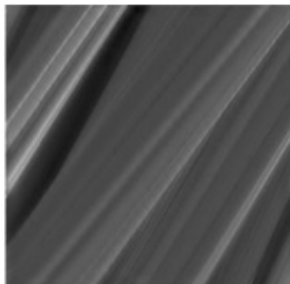
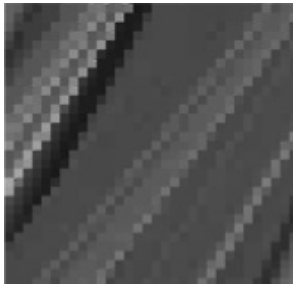
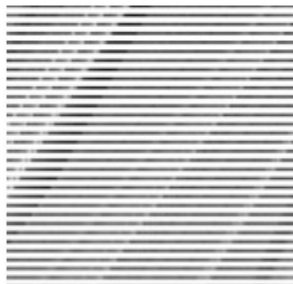
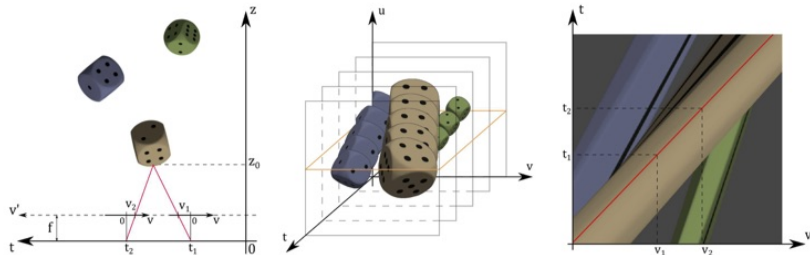
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Questions?

