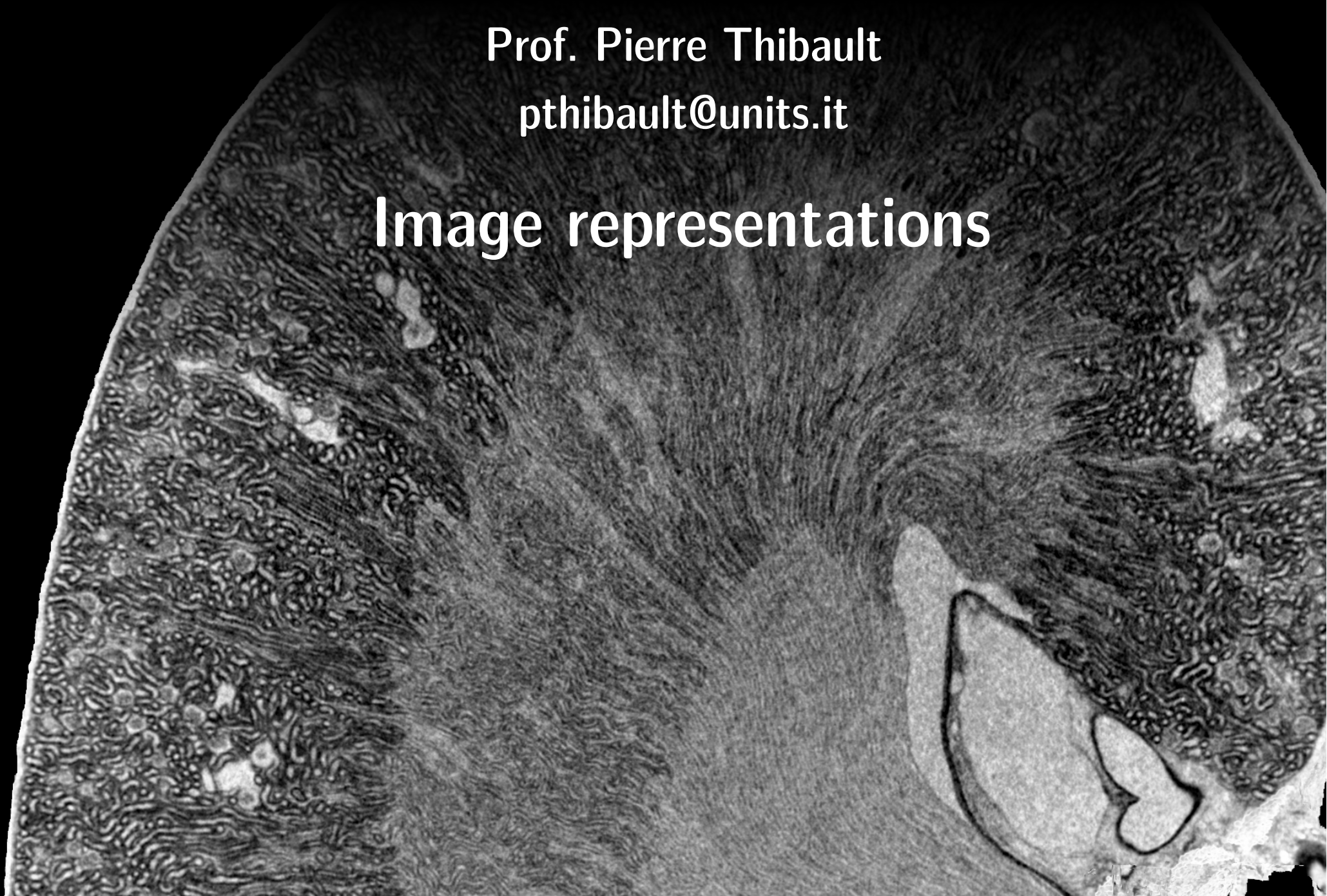


# Image Processing for Physicists

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## Image representations



# Overview

- The Discrete Fourier Transform as a change of basis
- Discrete Cosine Transform
- Windowed Fourier Transform
- Wavelet Transform
- (many others omitted!)

# Image representations

$$f(x, y) = \sum_n c_n B_n(x, y)$$

$c_n$ : coefficients

$B_n$ : basis functions

$\Rightarrow$  convenient; orthonormal

DFT:

$$f(m, n) = \sum_{k, l} F_{kl} \underbrace{e^{2\pi i \left( \frac{mk}{M} + \frac{nl}{N} \right)}}_{B_{kl}(m, n)}$$

shape of image is  $(M, N)$

$B_{kl}(m, n)$  DFT basis function

DFT (1D):  $z = e^{2\pi i / N}$

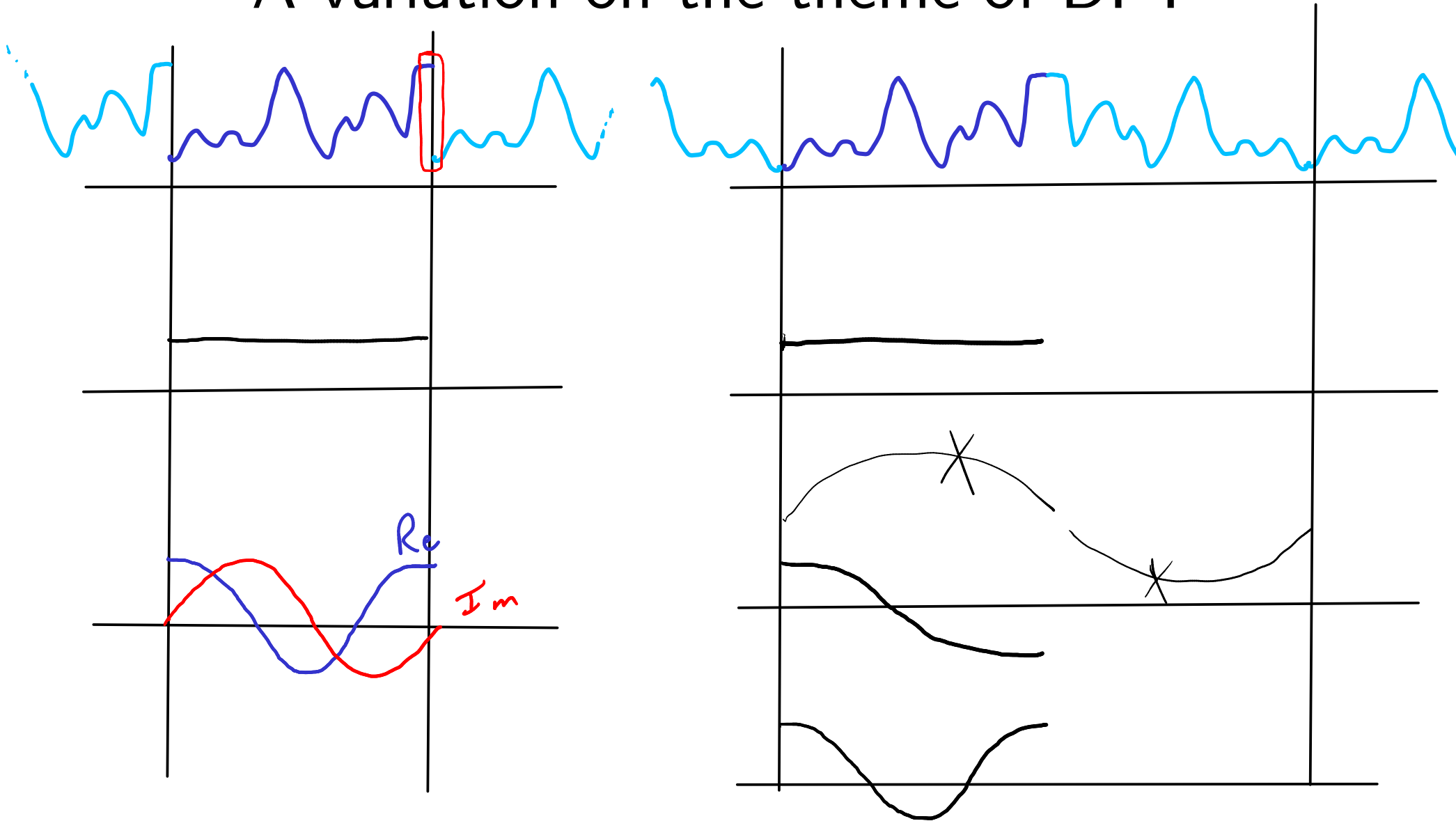
$$\left( \begin{array}{l} \langle kl | mn \rangle \\ \langle \vec{q} | \vec{x} \rangle = e^{i\vec{q} \cdot \vec{x}} \end{array} \right)$$

$$\begin{bmatrix} f \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \dots \\ 1 & z & z^2 & \dots \\ 1 & z^2 & z^4 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 1 & z^{N-1} & & \end{bmatrix} \begin{bmatrix} F \end{bmatrix}$$

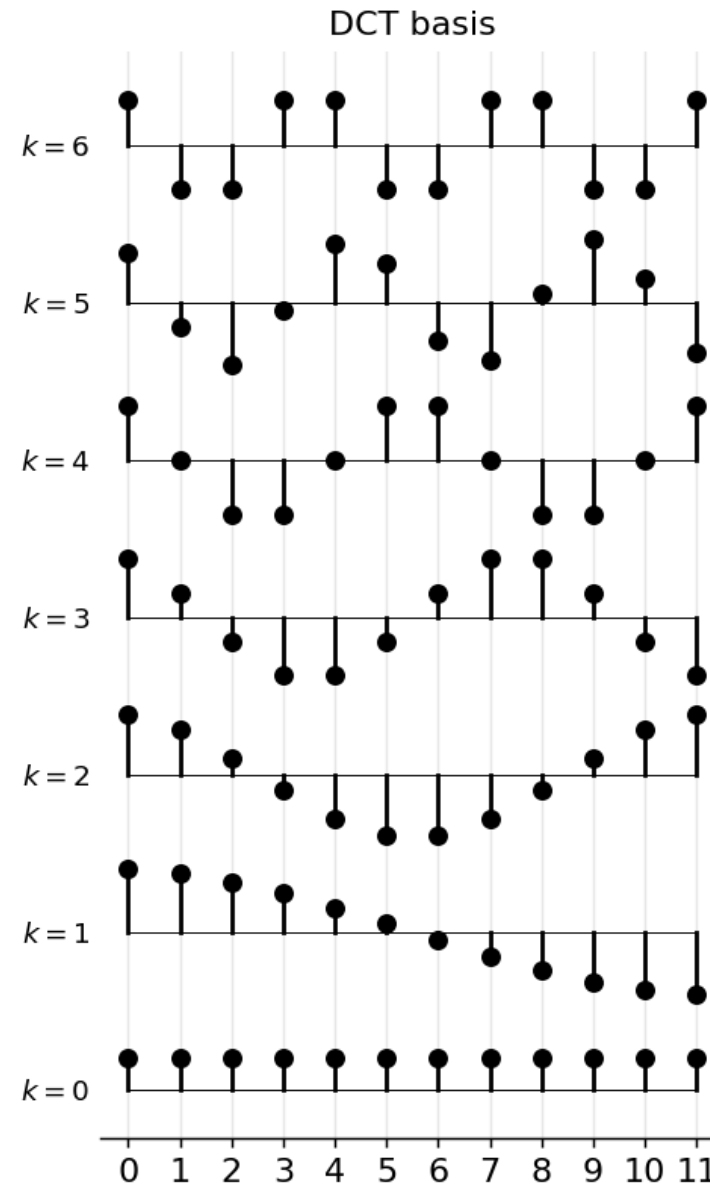
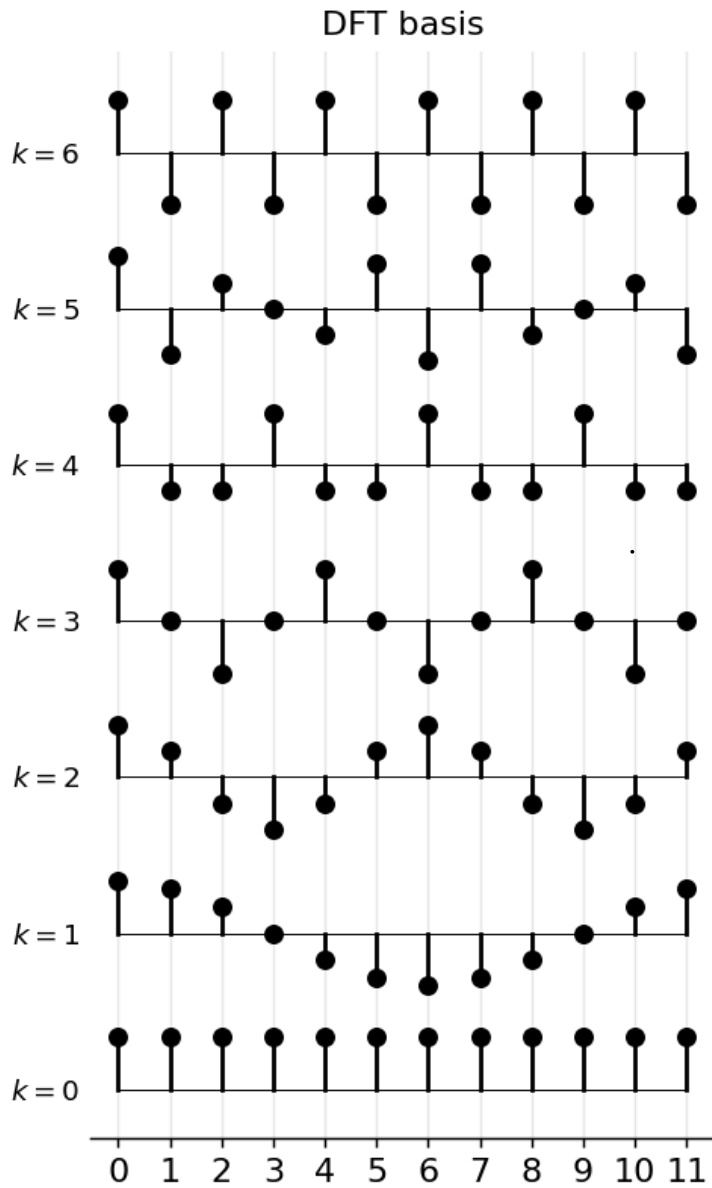
$$f_n = \sum_k F_k z^{nk} \quad \text{"z-transform"}$$

# Discrete Cosine Transform

A variation on the theme of DFT



# Discrete Cosine Transform

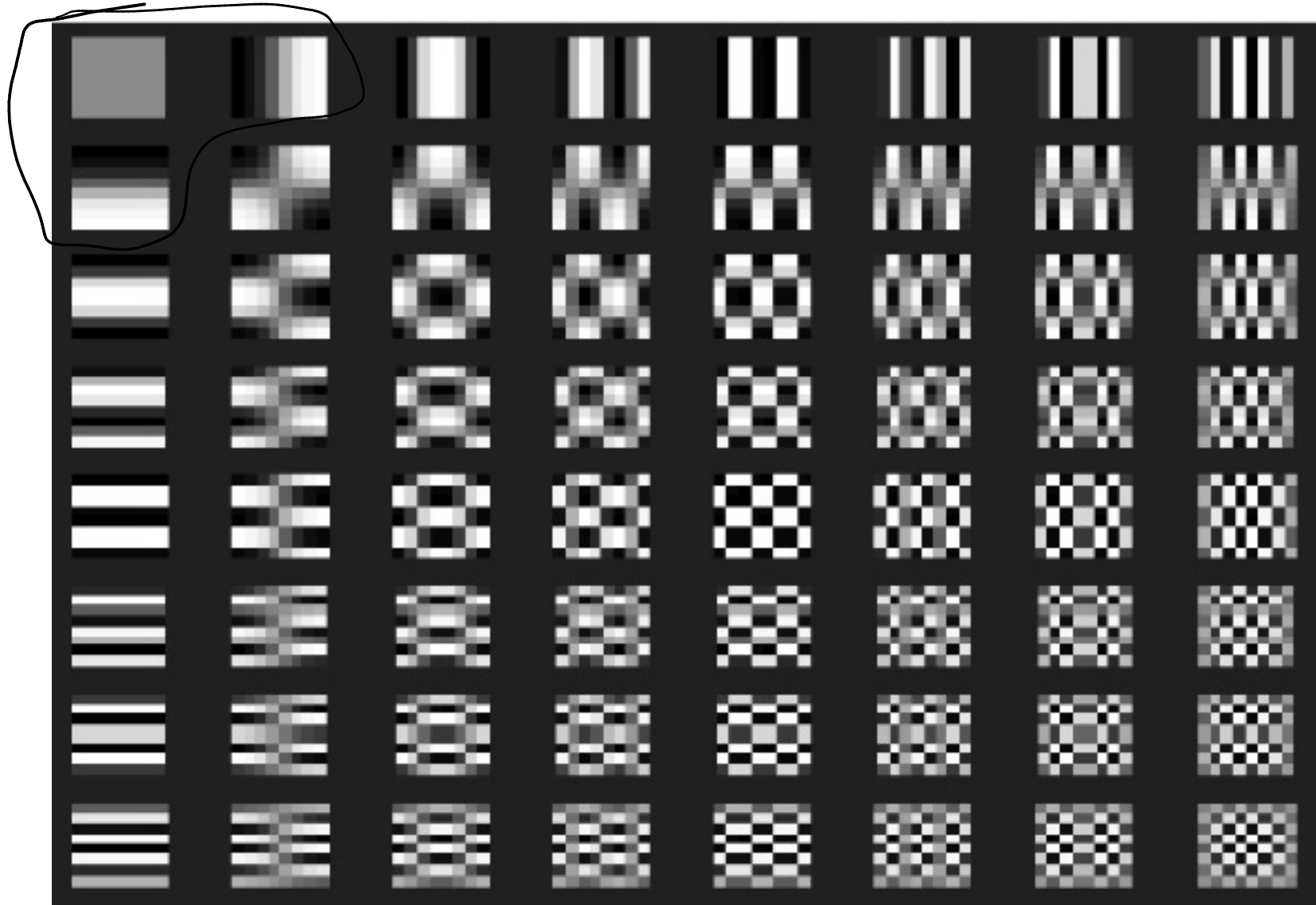


7 first  
basis functions

$N=12$

# Discrete Cosine Transform

64 DCT basis vectors for 8x8 image



# Discrete Cosine Transform

## Image compression



1:1 bit rate



8:1 bit rate



32:1 bit rate



128:1 bit rate

JPEG

← keeping  $\frac{1}{8}$  of the coefficients

Basis functions for DCT:

$$B_k^{(n)} = \cos\left((n + \frac{1}{2}) \frac{k\pi}{N}\right)$$

$$B_0^{(n)} = \frac{1}{\sqrt{2}}$$

# Historical overview

- 1822 Fourier: Fourier transform
- 1946 Gabor: “Gabor transform”, Short-time Fourier transform (STFT)
- 1974 Ahmed, Natarajan & Rao: Discrete Cosine Transform
- 1980s Morlet, Mallat, Daubechies, ... : Wavelets



# Bandpass filtering

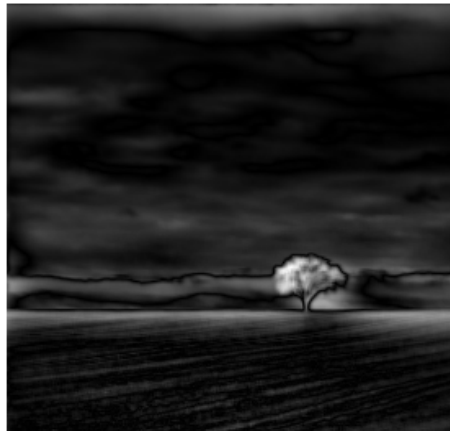
original



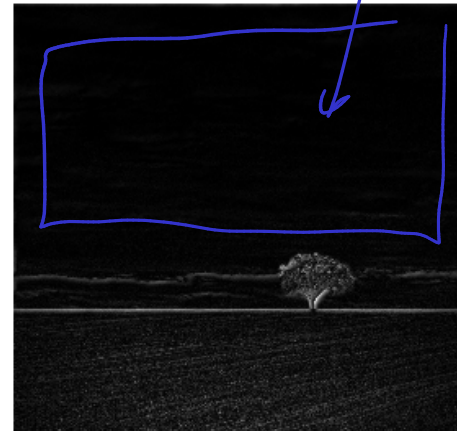
low pass



mid pass



high pass



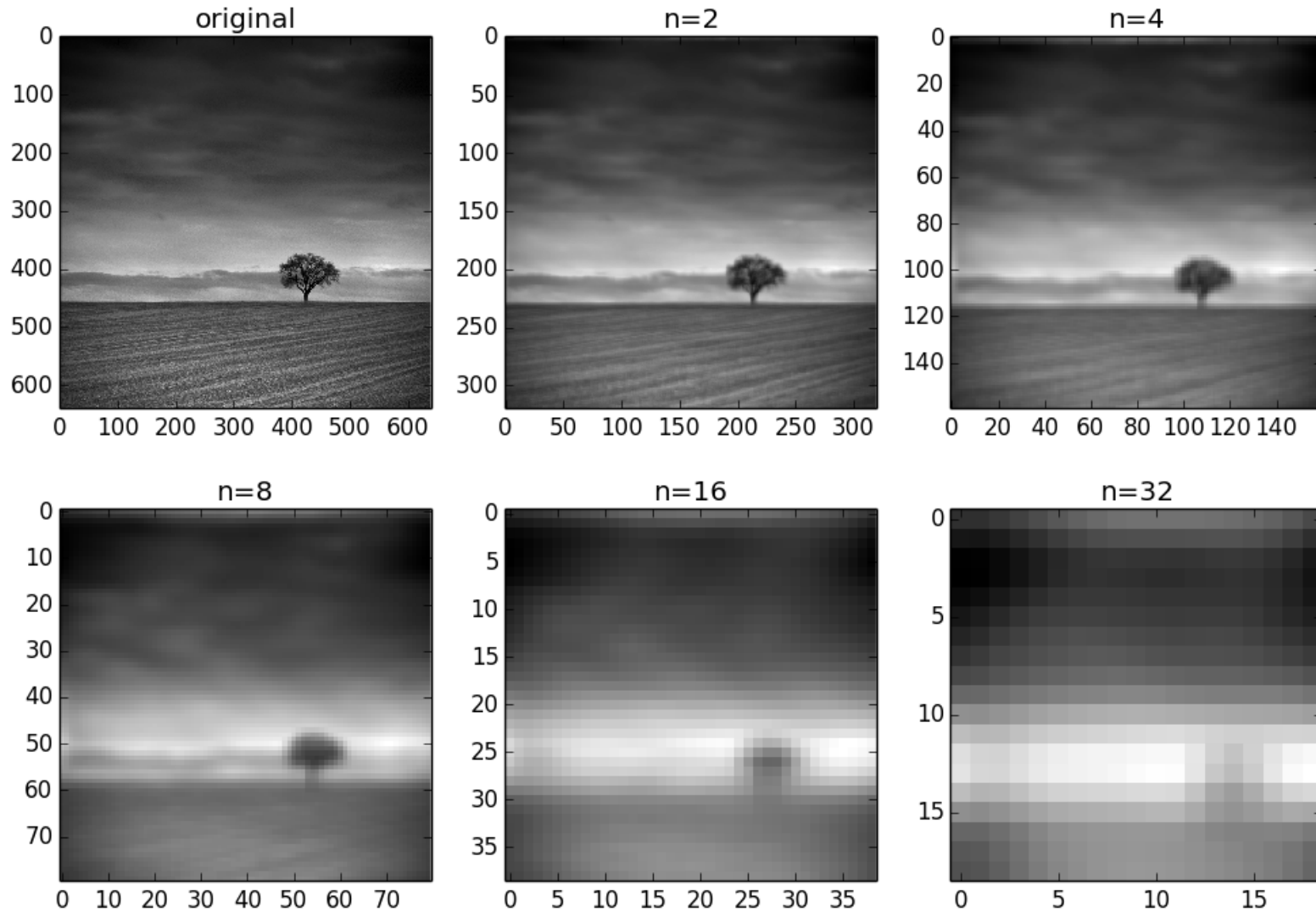
*no information*

Don't need high spatial resolution

Need high spatial resolution

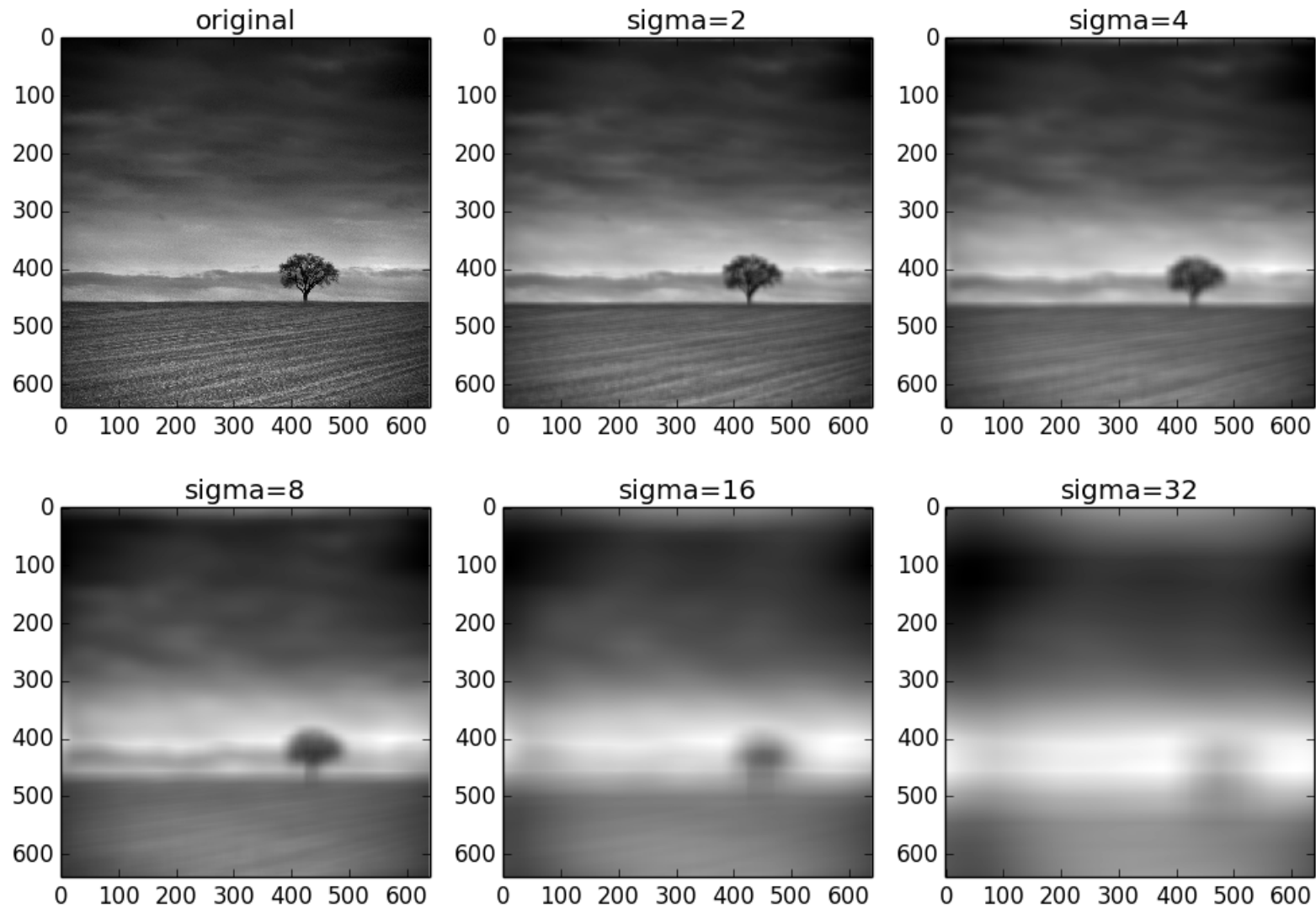
# Multiresolution analysis

Subsampling (taking every  $n^{\text{th}}$  pixel) successively reduces high frequency content



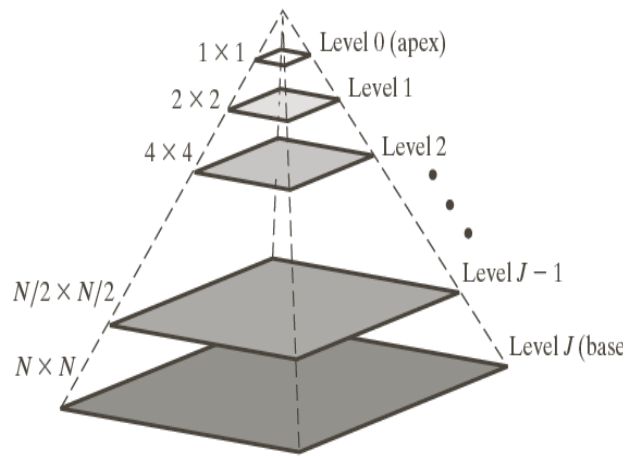
# Multiresolution analysis

Multiple filtering with Gaussian filters, sigma determines resolution



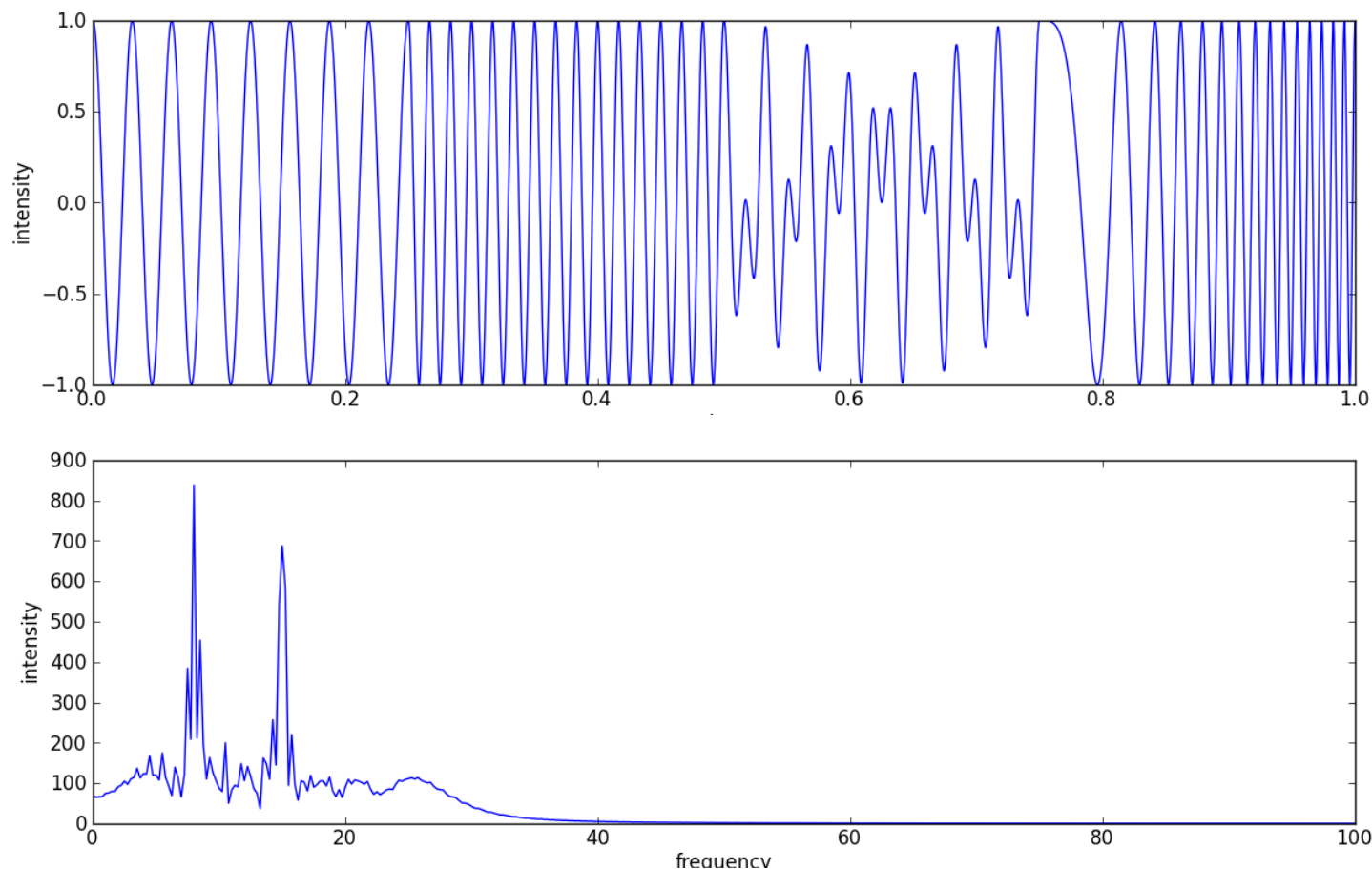
# Pyramid representation

Scale-space representation, pyramidal representation



# Stationary vs. non-stationary signals

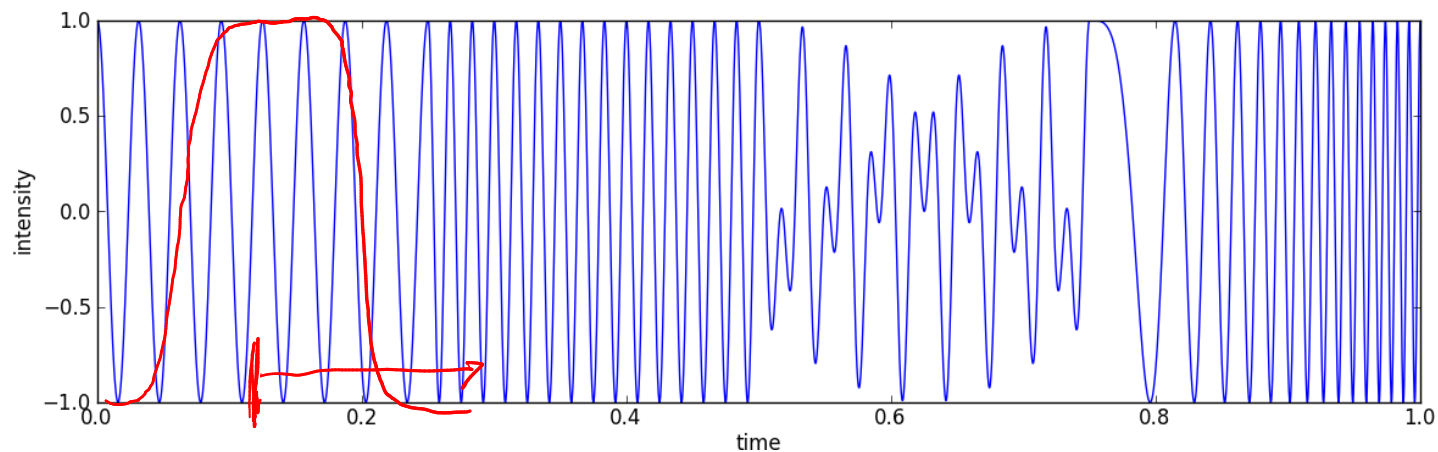
- Stationary signals: frequency doesn't change over time (spatially over the image)
- Non-stationary signals: frequency changes over time (spatially over the image)
- Examples of non-stationary signals: speech, most images



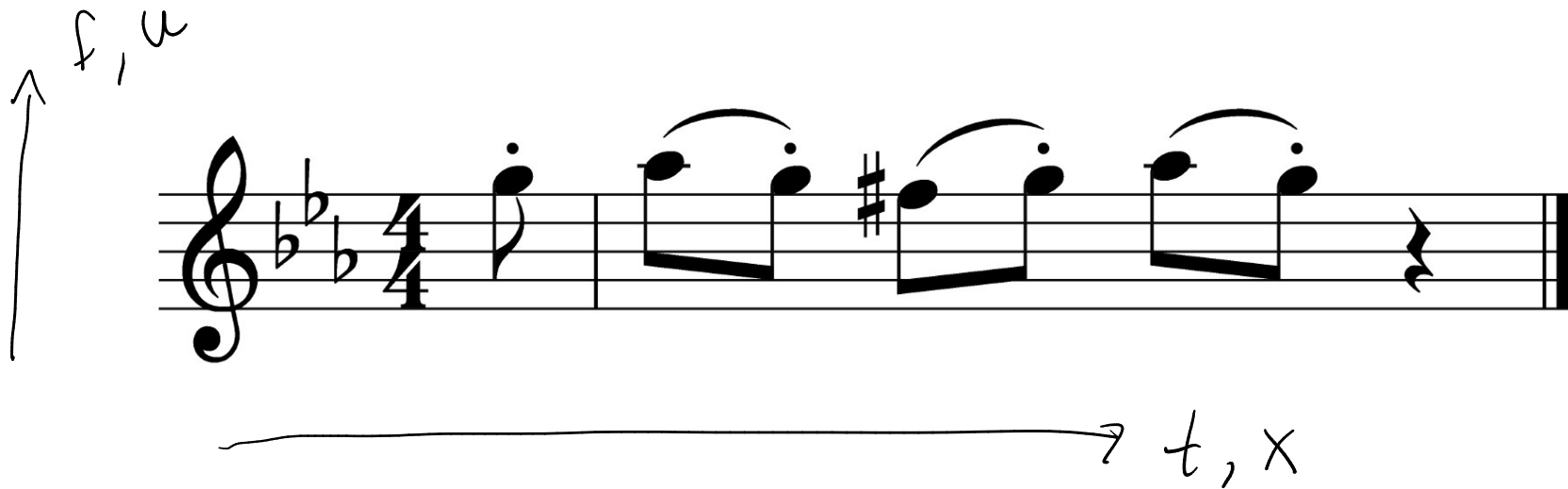
FT insufficient to localize the frequencies in our signal (image)

# Windowed Fourier transform

- Windowed Fourier transform is part of the field of “time-frequency analysis”
- Also known as Short-time Fourier Transform (STFT)
- Time-frequency representations are used in many different contexts (Audio, image processing/optics, quantum mechanics)
- Idea: slice up signal into small parts, analyze each separately
  - Multiply with window function  $w$  (of width  $d$ ) at position  $x_0$
  - Take Fourier transform of result
  - Slide window to new position
  - repeat



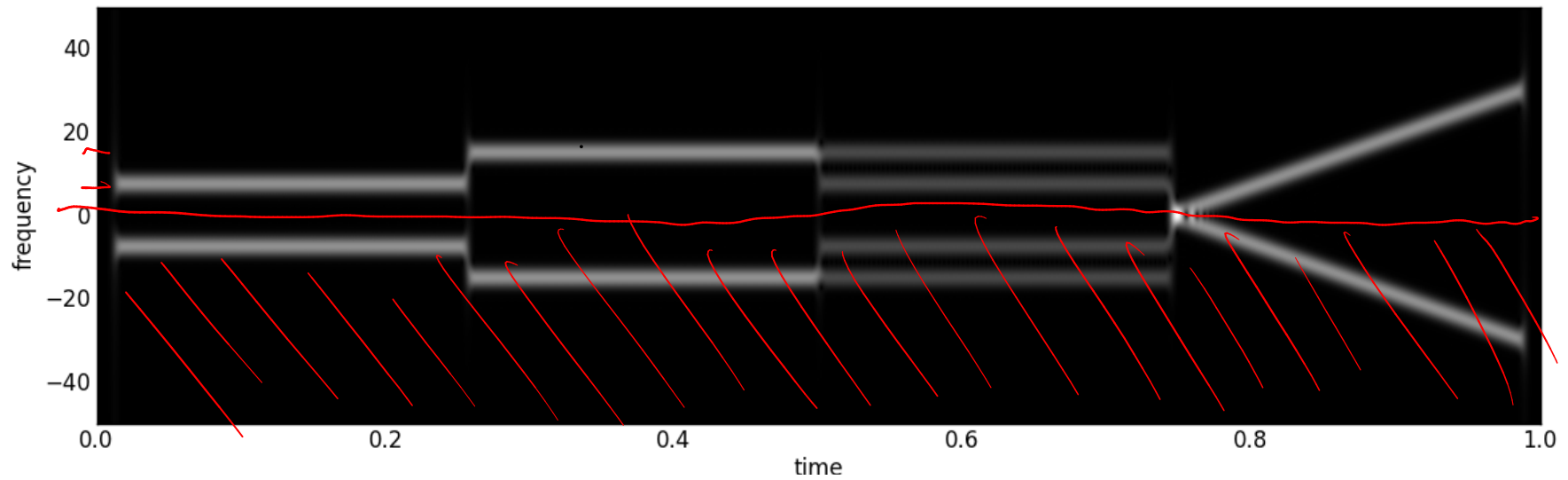
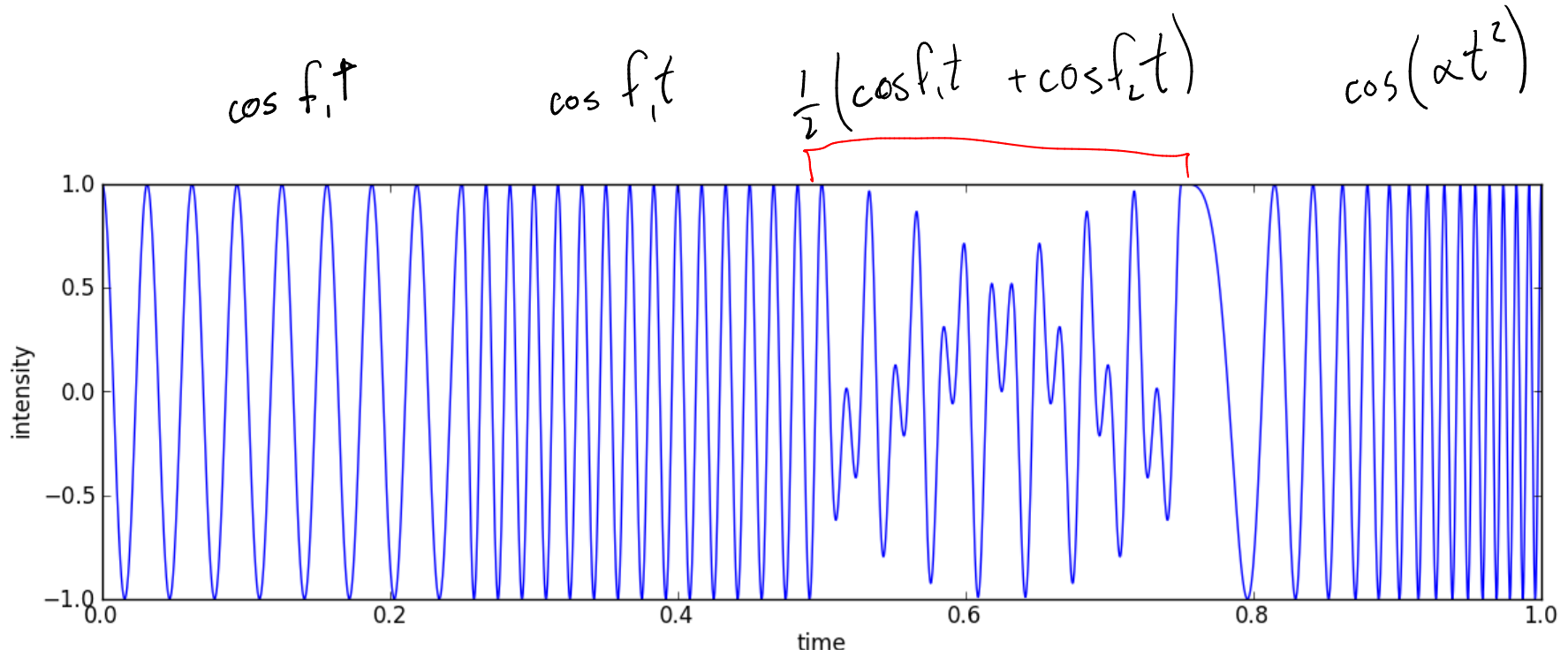
# Analogy to audio signals



spectrogram

$$S(u, x_0) = \int_{-\infty}^{\infty} \underbrace{f(x) w(x - x_0)}_{\text{waveform}} e^{-2\pi i u x} dx$$

# Spectrogram

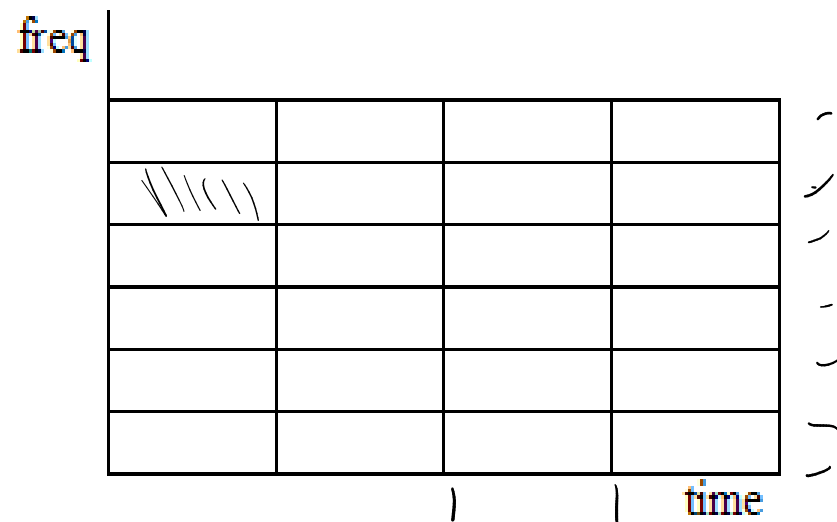
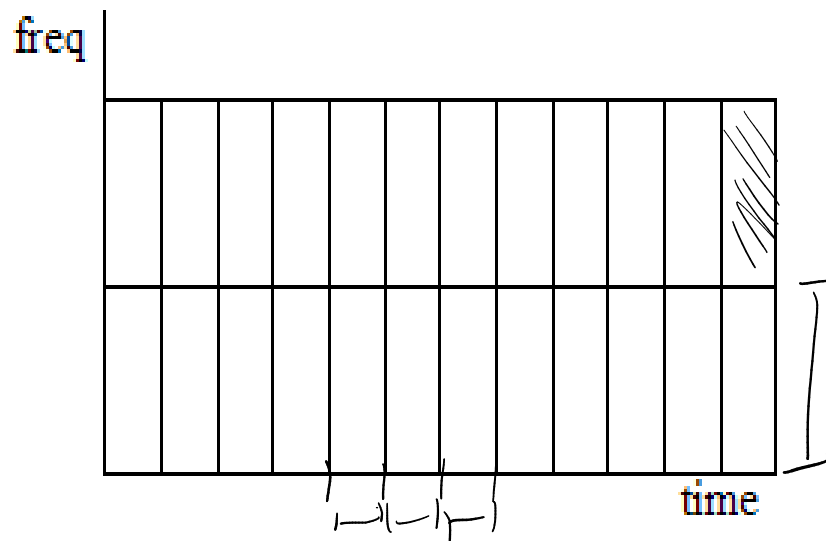




# Uncertainty relation

$$\sigma_s \sigma_f \geq \frac{1}{4\pi}$$

- Finite area in the time-frequency plane



- This is limitation of WFT and hence development of **wavelets**



# Continuous wavelet transform (WT)

- Parameters: translation and scaling

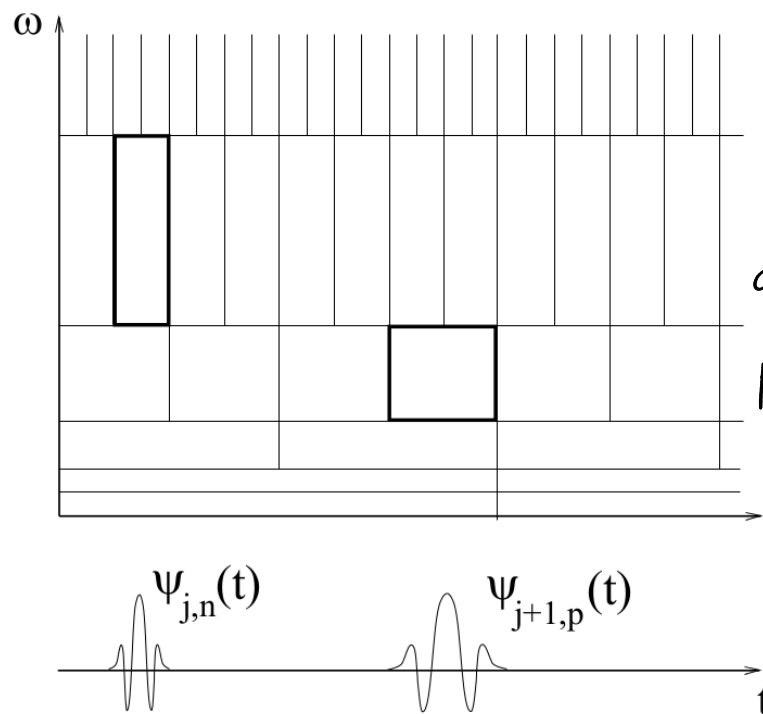
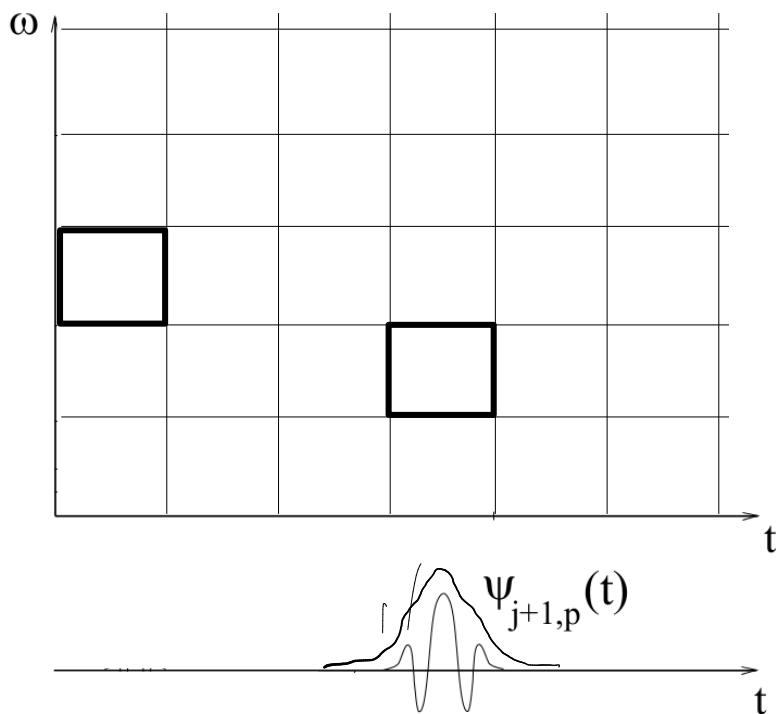
$$WT_{s, x_0} \{ f \} = \int_{-\infty}^{\infty} f(x) \psi_{s, x_0}(x) dx$$

↑ position
↓ wavelets

$$\psi_{s, x_0} = \frac{1}{\sqrt{s}} \psi\left(\frac{x-x_0}{s}\right)$$

↑ scale
↑ mother wavelet

- Analyze signal at different scales instead of different frequencies



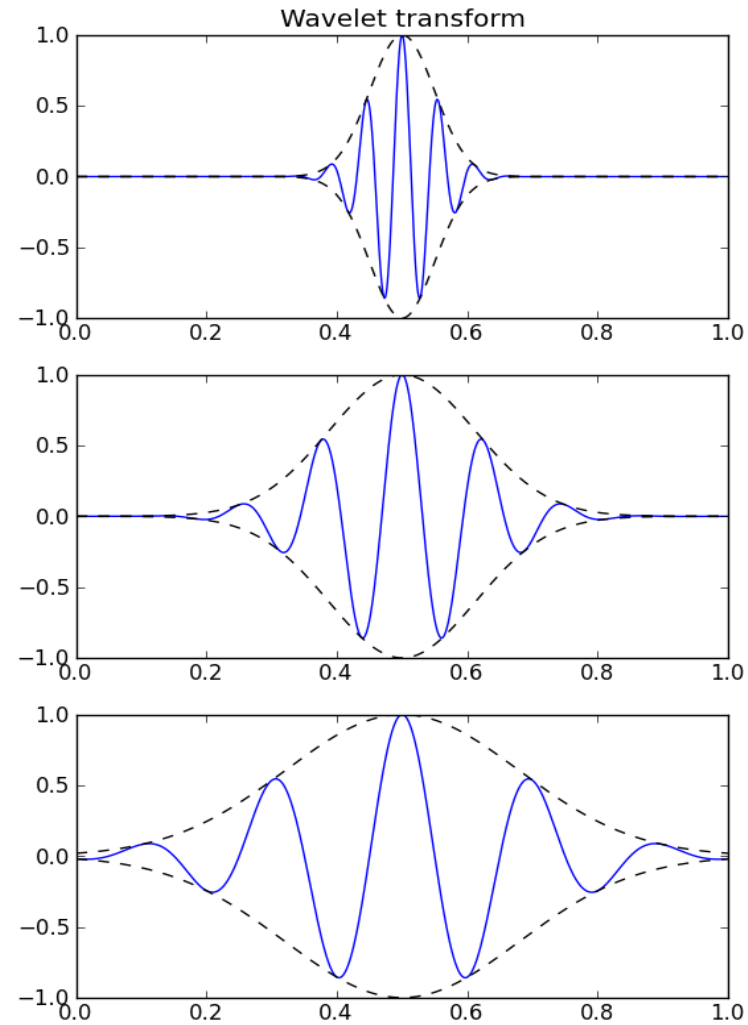
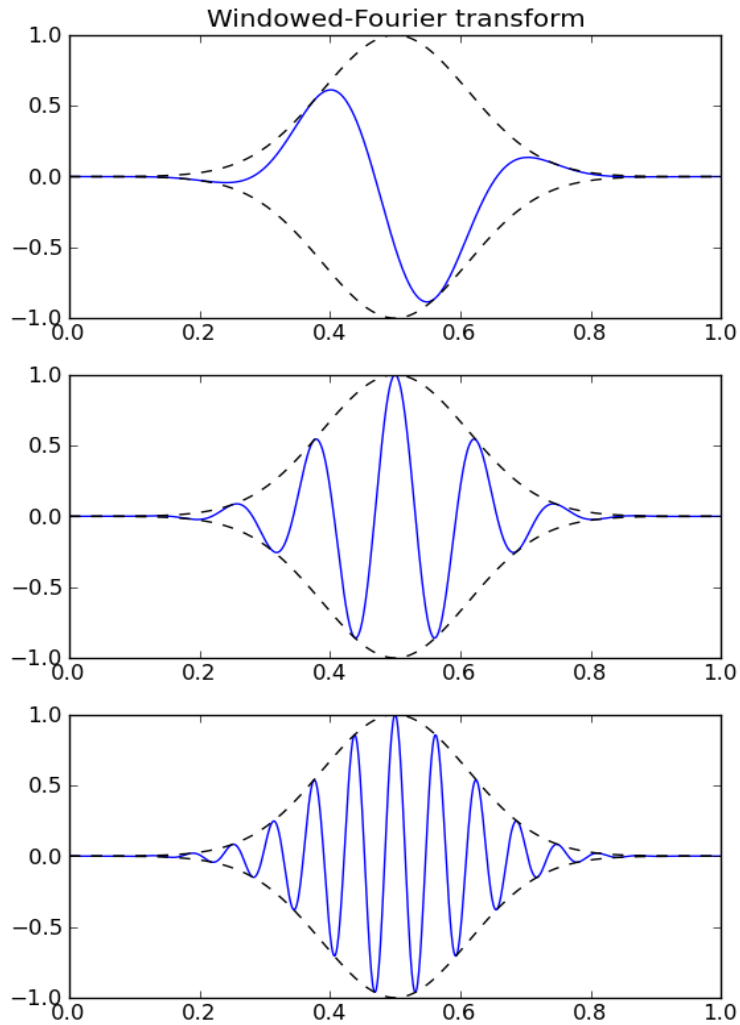
scaling gives convenient partitioning of phase space

Source: Mallat, "A wavelet tour of signal processing"

# WFT vs WT

WFT - keep window width constant  
- change modulation

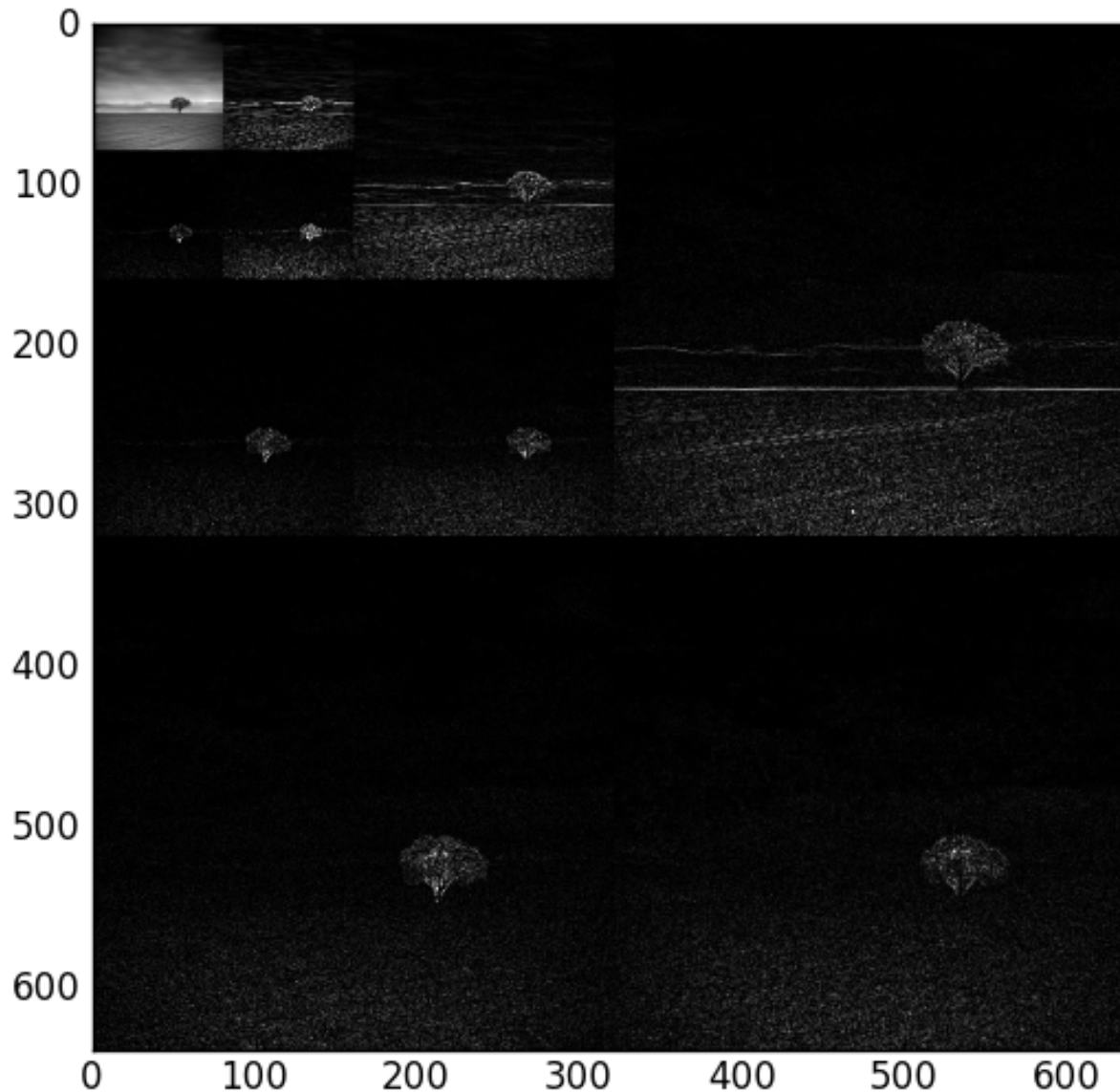
Wavelet - keep shape constant  
- change scale



# Discrete Wavelet decomposition of image

- Perform each DWT, collect and tile all coefficients
- Here: 3 level decomposition

*used for instance  
as a way to  
impose sparsity  
of a signal/image*



# Summary

- Images can be represented by different basis functions.
- Fourier basis: localized in frequency, delocalized in real space.
- Windowed Fourier Transform: localized – to some extent – in both spaces
- Wavelet analysis decomposes a signal in position and scale (instead of position and frequency as for WFT).
- Sparse representations are representations in which the image content is represented by a few relevant coefficients, while the other <sup>(pixels)</sup> <sub>values</sub> are close to zero
- Sparse representations have advantages for compression, denoising, ...  
*regularizers, ...*