The background features a large, faint watermark of the University of Pisa crest, which includes a face and the Latin motto 'ANNO DOMINI MCCCXLIII'.

# Wavelets

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INTELLIGENT SYSTEMS FOR PATTERN RECOGNITION (ISPR)

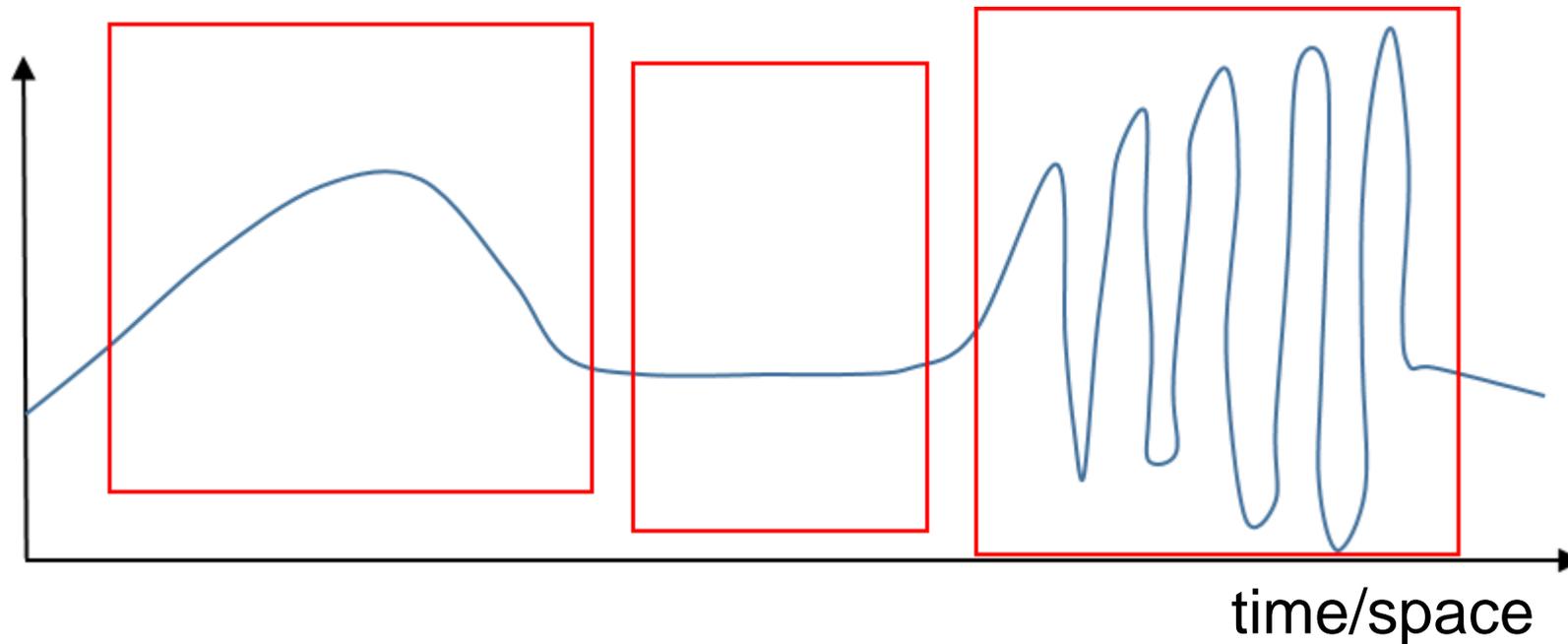
DAVIDE BACCIU – DIPARTIMENTO DI INFORMATICA - UNIVERSITA' DI PISA

DAVIDE.BACCIU@UNIFI.IT

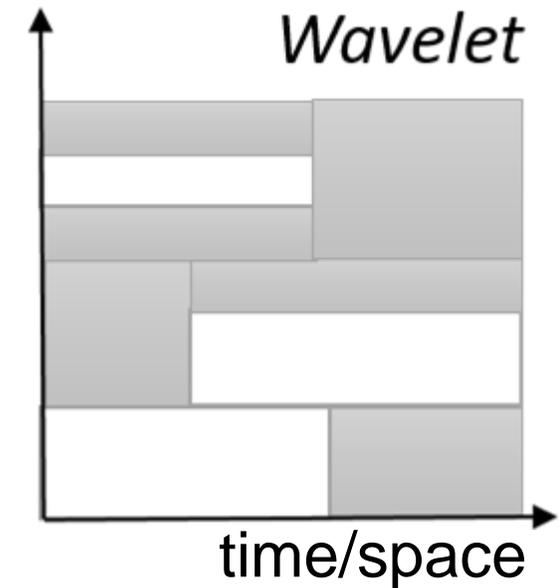
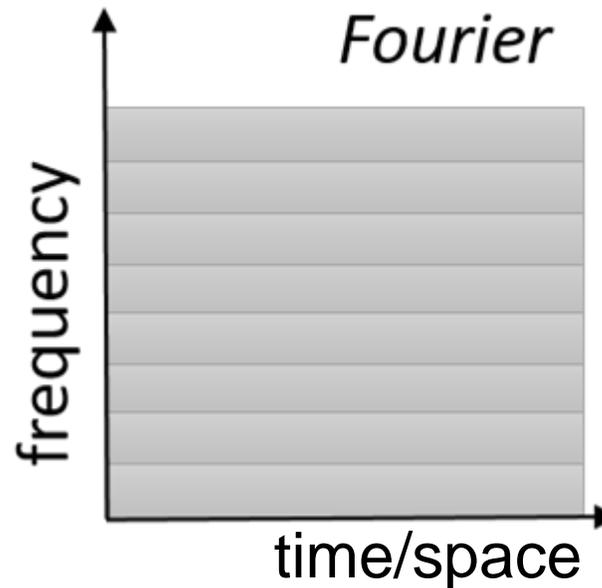
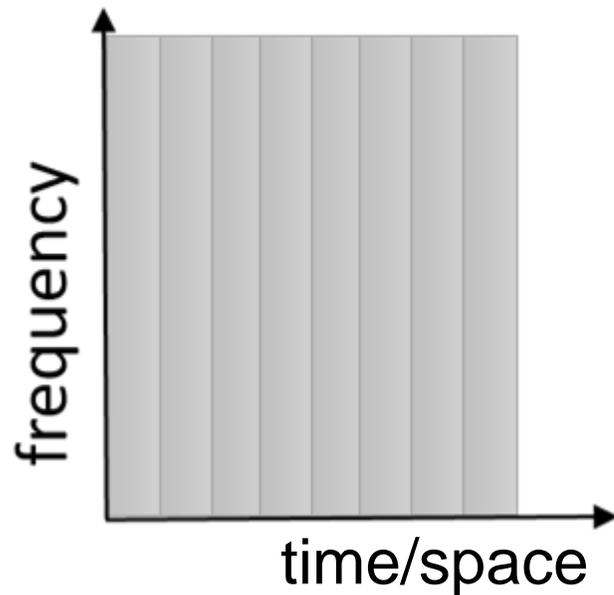
# Limitations of DFT

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Sometimes we might need localized frequencies rather than **global frequency analysis**

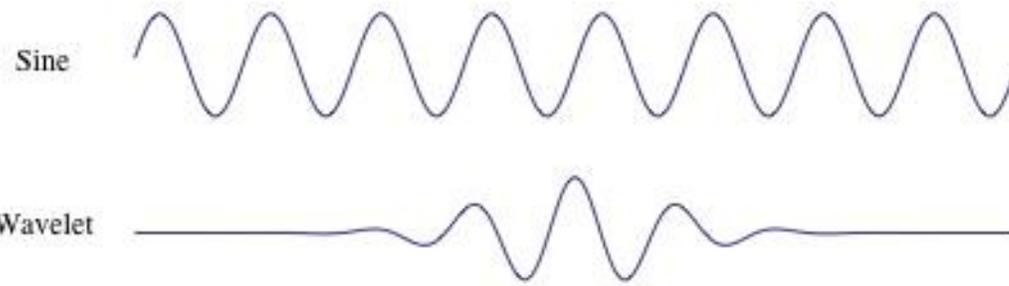


# Graphical Intuition



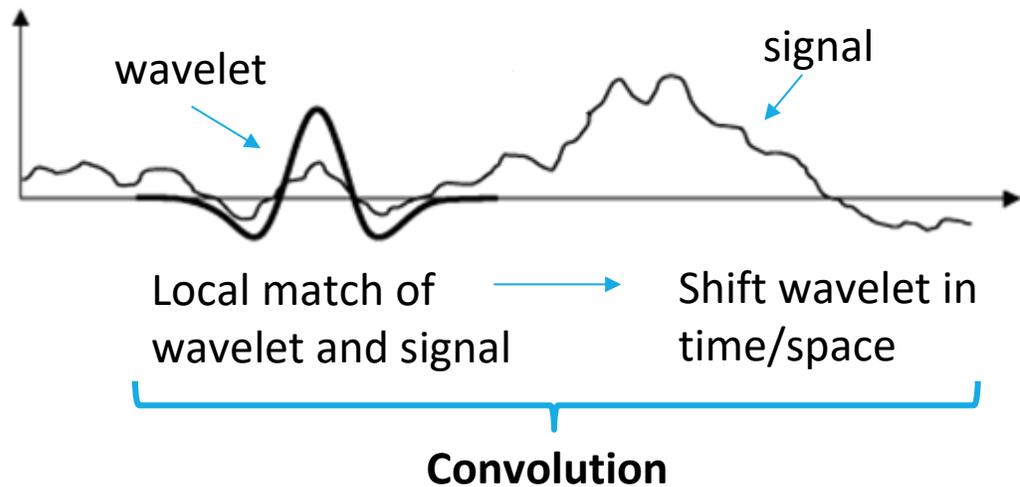
Split signal in frequency bands only if they exist in specific time-intervals or portion of the space

# How Does it Work?



Basis function upon which to decompose the signal in **Fourier transform**

Basis function upon which to decompose the signal in **wavelet transform**



1. Scale and shift original signal
2. Compare signal to a wavelet
3. Compute a coefficient of similarity



# Wavelets

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Split the signal using an orthonormal basis generated by **translation and dilation** of a **mother wavelet**

$$\sum_t \mathbf{x}(t) \Psi_{j,k}(t)$$

Terms  $k$  and  $j$  regulate scaling and shifting of the wavelet

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{2^k}} \Psi((t - j)/2^k)$$

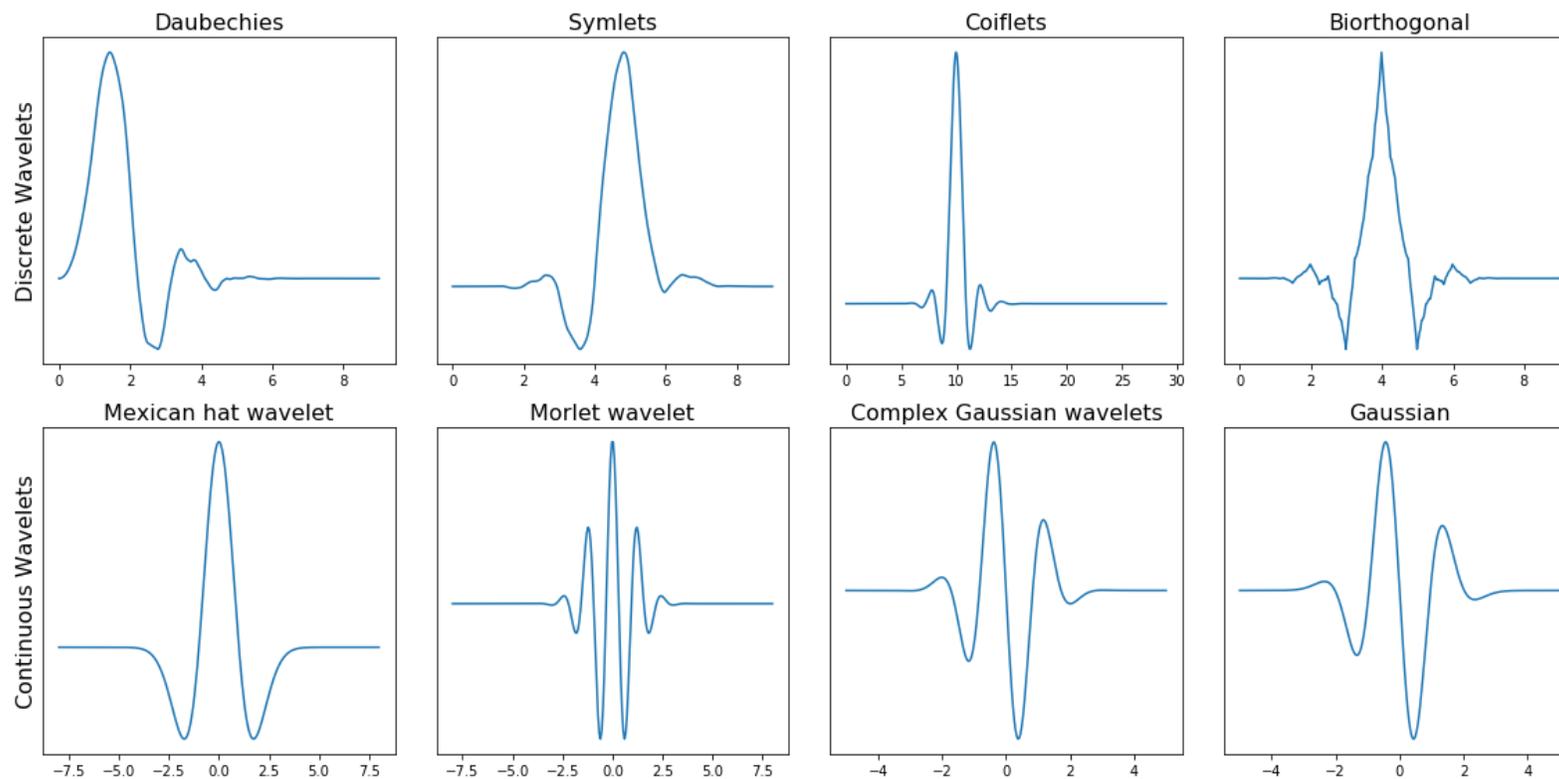
with respect to the mother  $\Psi(\cdot)$ .

- $k < 1$  Compresses the signal
- $k > 1$  Dilates the signal

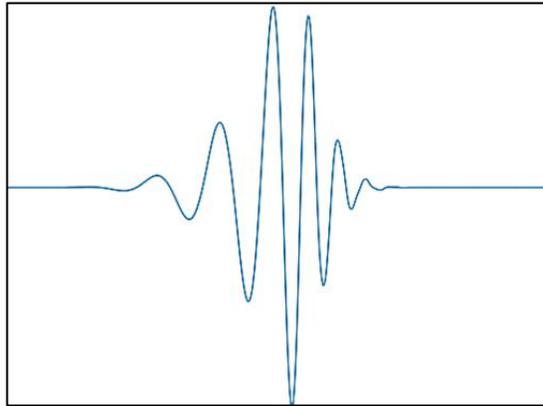


# A (partial) wavelet dictionary

Many different possible choices for the mother wavelet function

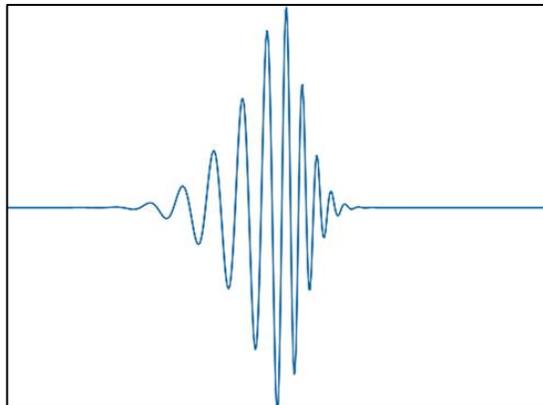


# Scaling/dilation is akin to (sort of) frequency



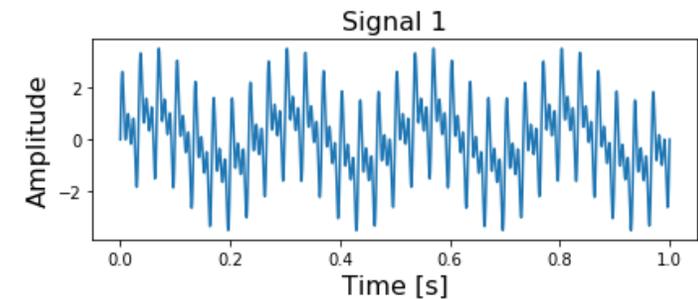
## High scale

- Stretched wavelet
- Slowly changing, coarse features
- Low frequency

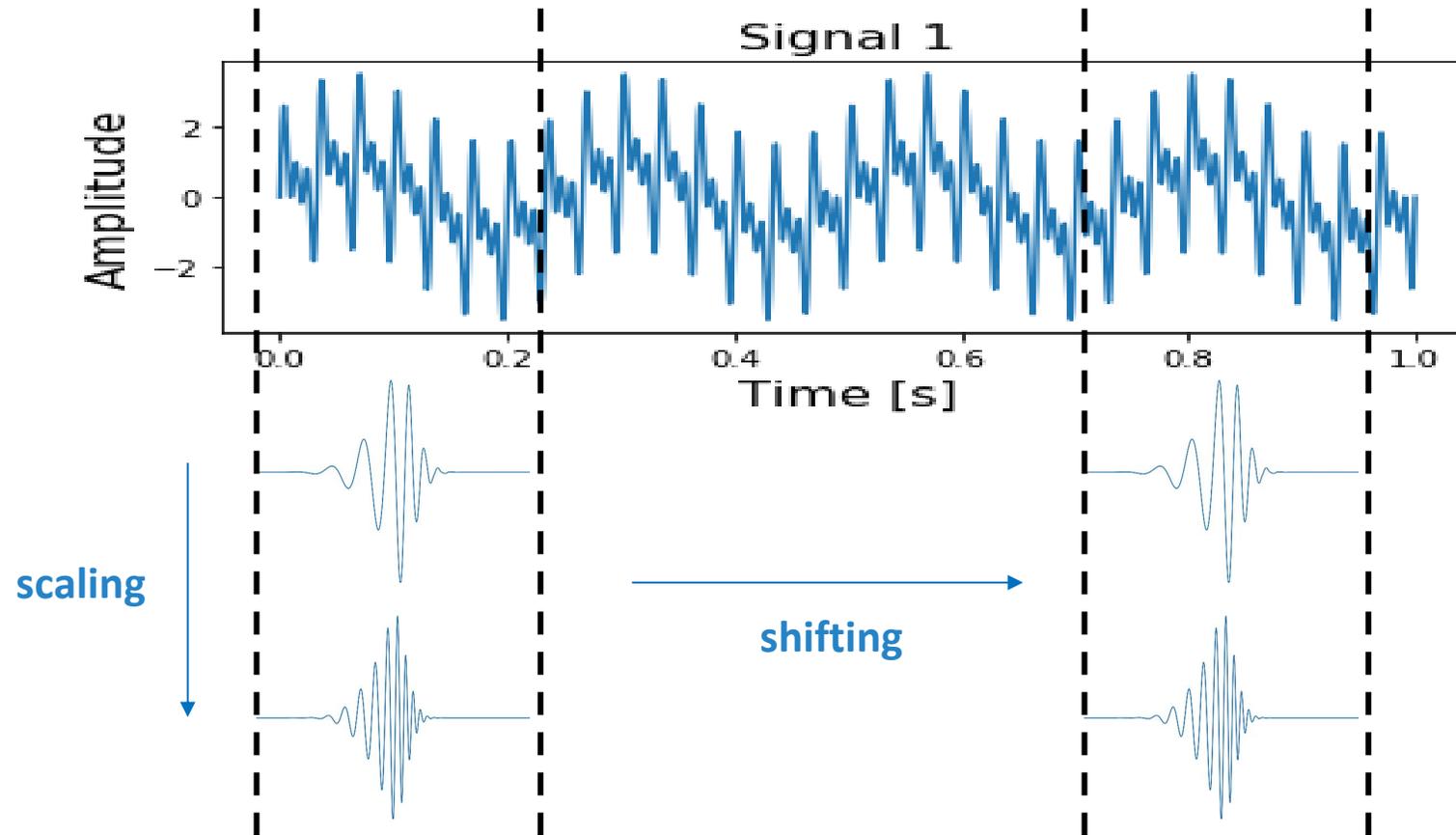


## Low scale

- Compressed wavelet
- Rapidly changing details
- High frequency

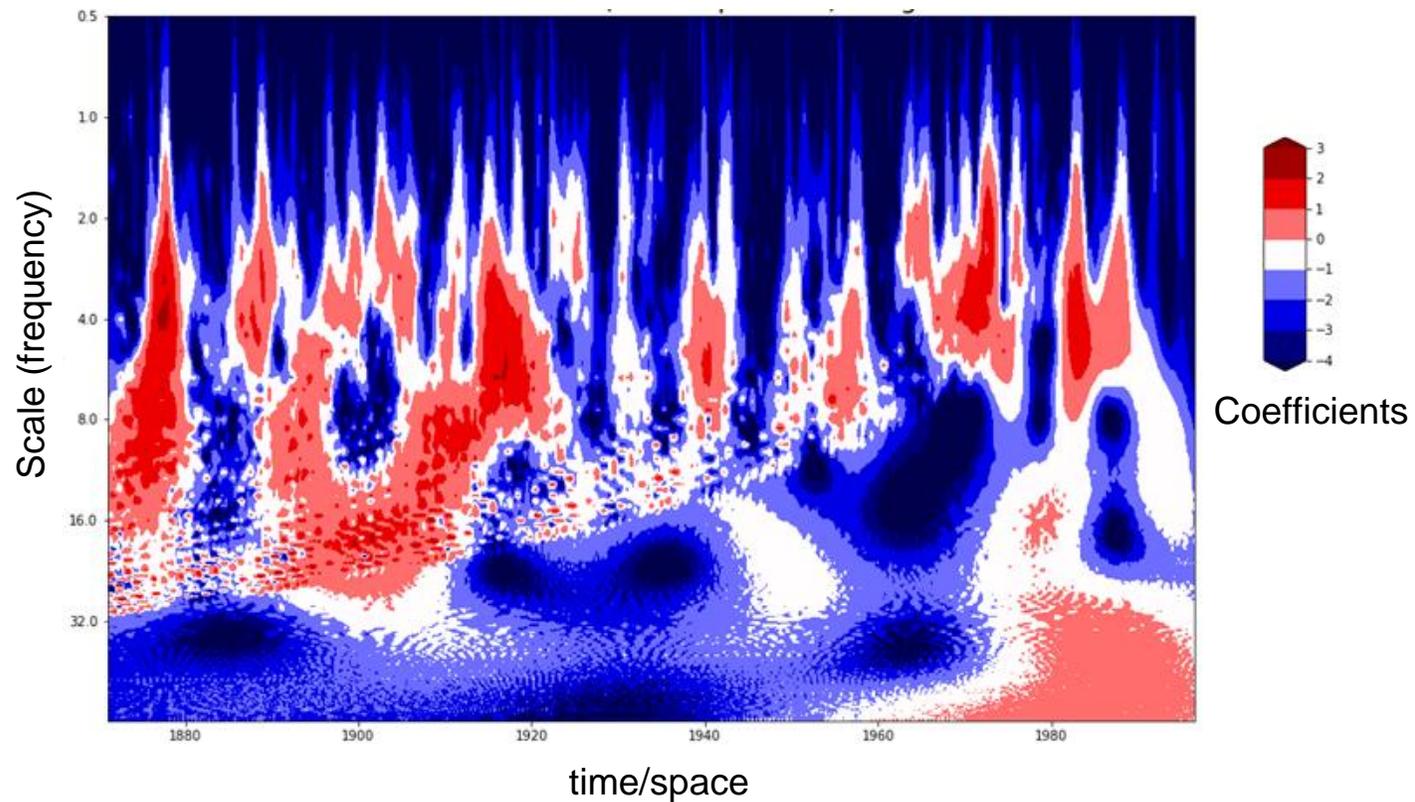


# Shifting moves the wavelet in time/space on the signal



Compute coefficients of signal-wavelet match across all scales and shifts

# Coefficient Plot



This is once-again the **power-spectrum** of the signal, revealed by the (continuous) **Wavelet Transform**

# Discrete Wavelet Transform (DWT)

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- Use a **finite set of scales and shifts** rather than “any possible value” as in the continuous wavelet transform
- Subset scale continuous values **using power-of-two values with step 1** (and translates proportionally to scale if **decimated**)
- **Key aspects**
  - Efficient and sparse representation
  - Orthonormal basis
  - Can always be inverted



# Using the WT in PR Applications (I)

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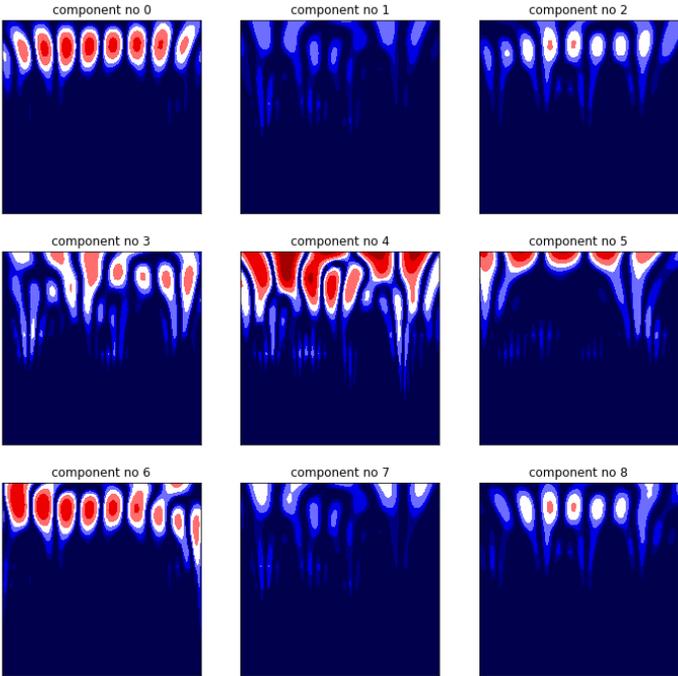
Human Activity Recognition Using Smartphones Dataset  
(Reyes-Ortiz et al, 2012)



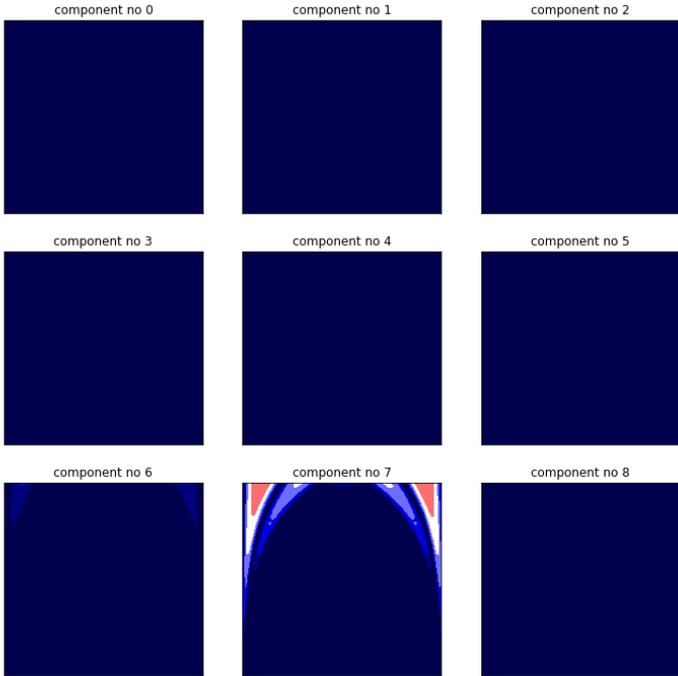
9-components sensor measurements of people doing different activities (walking, laying, standing, ...)

# Using the WT in PR Applications (II)

Activity: walking upstairs



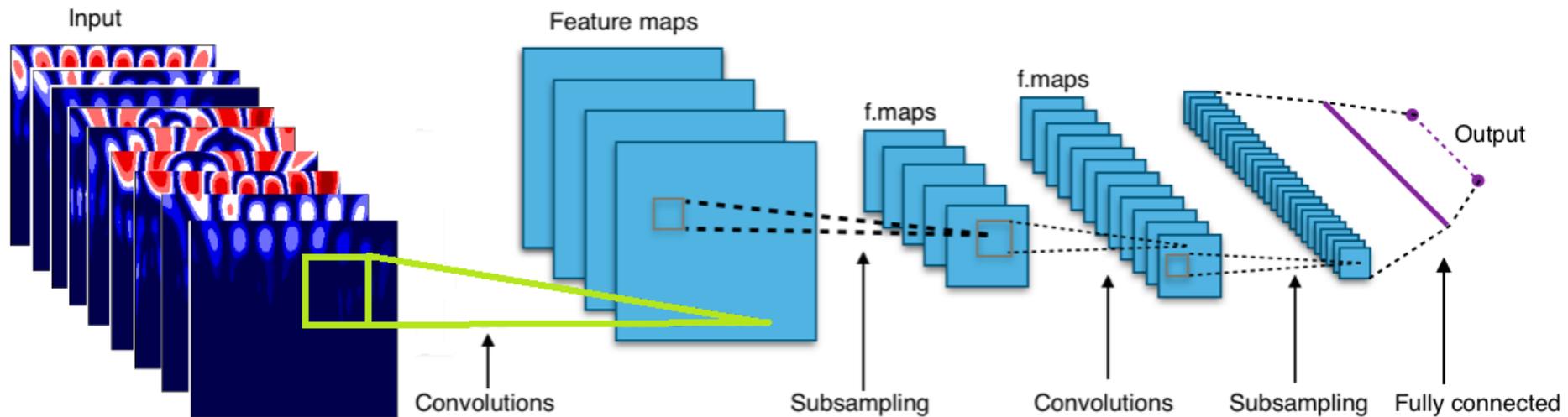
Activity: laying



Spectrograms for different activities alone lead to a classification accuracy of 0.91



# Using the WT in PR Applications (III)



Using wavelet transform + convolutional neural networks  $\Rightarrow$  0.96

# Code

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- [PyWavelets](#) - Wavelet transforms in Python
- [Wavelet Toolbox](#) – Wavelet transforms in Matlab



# Take Home Messages

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- Fourier transform
  - Basis functions: sinusoids
  - Only offers frequency information
- Wavelet transforms
  - Basis functions: small waves (wavelets)
  - Frequency and temporal/spatial information
- Wavelets can be more effective on discontinuous and bursty data



# Next Lecture

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## Generative and Graphical Models

- Introduction to a module of 15 lectures
- A refresher on probabilities
  - Probability theory
  - Conditional independence
  - Inference and learning in generative models
- Graphical models representation
- Directed, undirected and dynamic graphical models

