

# Welcome to Time-Frequency Analysis, Adaptive Filtering and Source Separation

**Lecture 5: Discrete Wavelet Transform  
MultiResolution Analysis**

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## Power spectra

- ❑ Classical methods
- ❑ Modern approaches
  - Parametric methods
  - Non parametric
- ❑ Time Frequency analysis
  - Time-frequency methods
  - Time-scale methods (**WAVELET**)

# From surface to deep learning



**Storyline**



**Questions and Answers**

Each group will come up with 2 questions on CWT.  
I will pick one member to read the questions for the audience. Each group will work on the answers during the exercises time.

## Wavelet transform

- None of the methods developed so far has solved the time-frequency problem without constraints or added artifacts.
- Fourier transform
- $F(m) = \int_{-\infty}^{+\infty} x(t) \cdot e^{-j2\pi mt} dt$
- A sine wave is perfectly localized in frequency, but infinite in time.

## Short-time fourier transform

$$STFT(t, f) = \int_{-\infty}^{+\infty} x(\tau)w(t - \tau)e^{-j2\pi f t} d\tau$$

In general

$$X(t, m) = \int_{-\infty}^{+\infty} x(\tau) \cdot f(t - \tau)_m d\tau$$

In the wavelet transform (WT), family members consist of enlarged and compressed versions of the basic function

## Continuous Wavelet Transform (CWT)

From french: ondelette (small wave)

➤ Finite in time

➤ 
$$W(a, b) = \int_{-\infty}^{+\infty} x(t) \cdot \frac{1}{\sqrt{a}} \psi^* \left( \frac{t-b}{a} \right) dt$$

➤ Different values of  $a$  and  $b$  gives a serie of wavelets that may be added together to reconstruct the signal

➤ **They are all localized in both time and frequency, but not precisely localized in either.**

# Continuous Wavelet Transform (CWT)

## CWT

$$\text{➤ } W(a, b) = \int_{-\infty}^{+\infty} x(t) \cdot \frac{1}{\sqrt{a}} \psi^* \left( \frac{t-b}{a} \right) dt$$

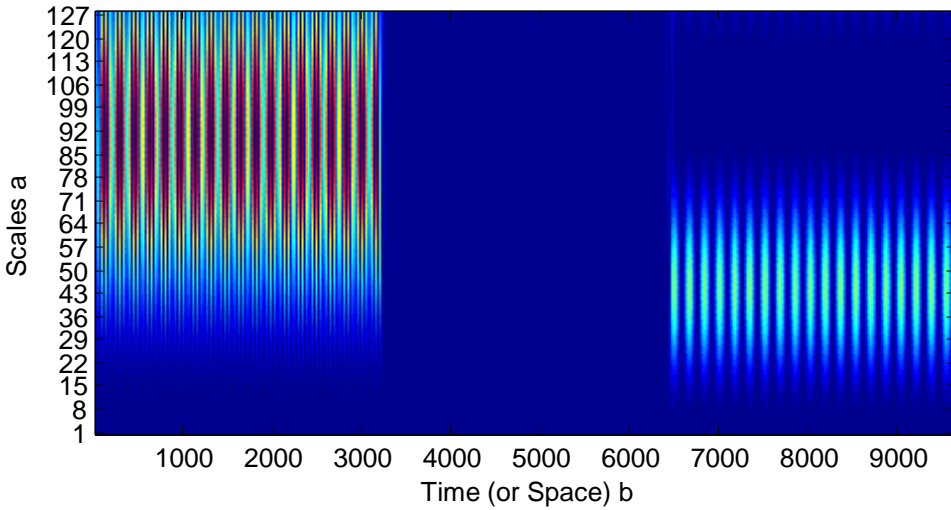
## iCWT

$$\text{➤ } x(t) = \frac{1}{C} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W(a, b) \cdot \psi^*(t) da db$$

# Solutions

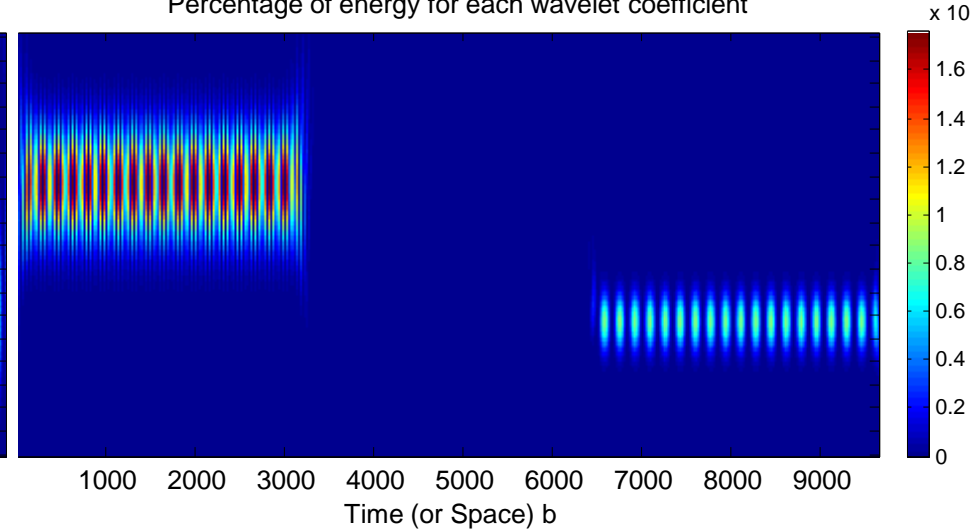
**HAAR Wavelet**

Percentage of energy for each wavelet coefficient



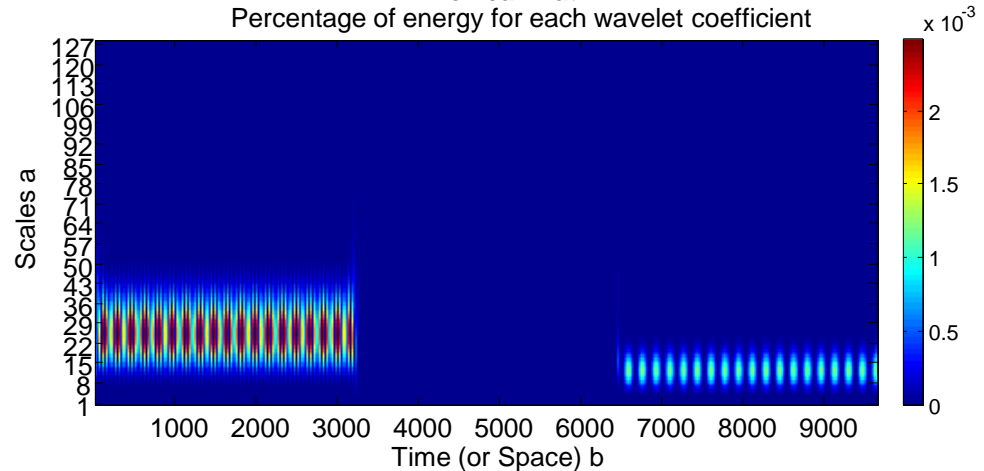
**Morlet**

Percentage of energy for each wavelet coefficient

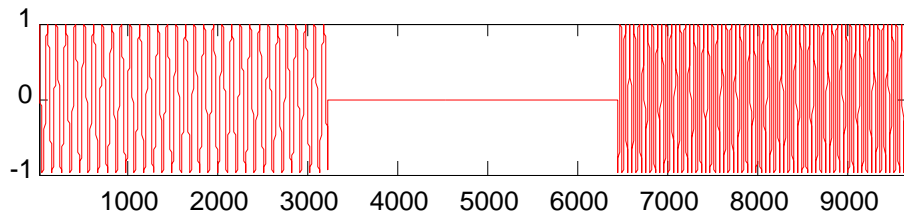


**Mexican hat**

Percentage of energy for each wavelet coefficient



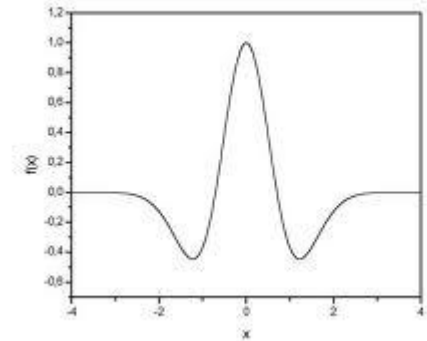
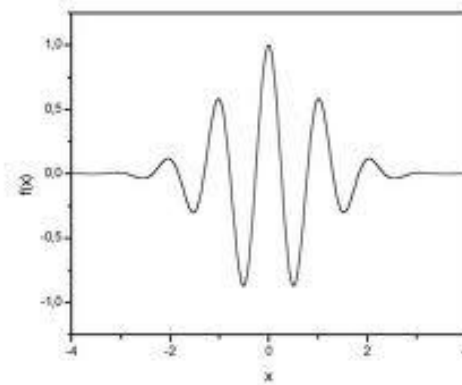
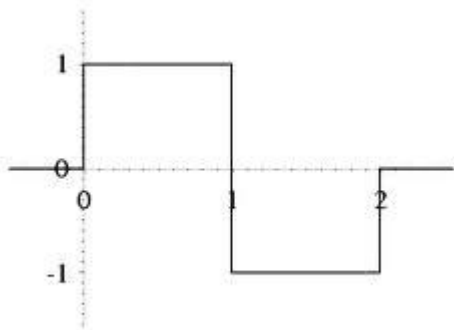
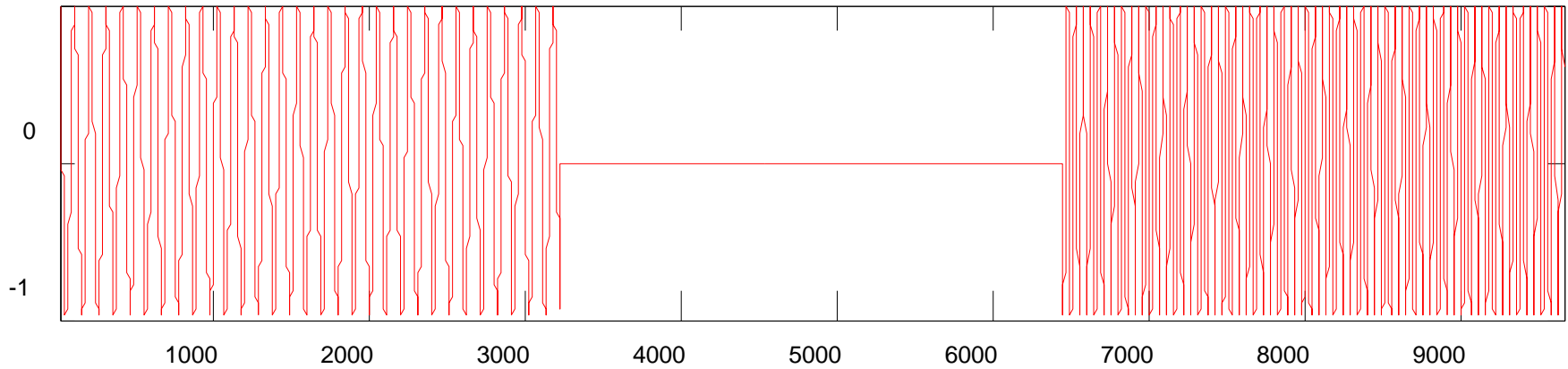
**Analyzed Signal**





# Solutions

1



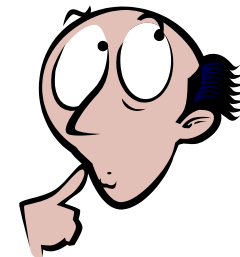
# Discrete Wavelet Transform (DWT)

From CWT  $\longrightarrow$  DWT

Why CWT and DWT?

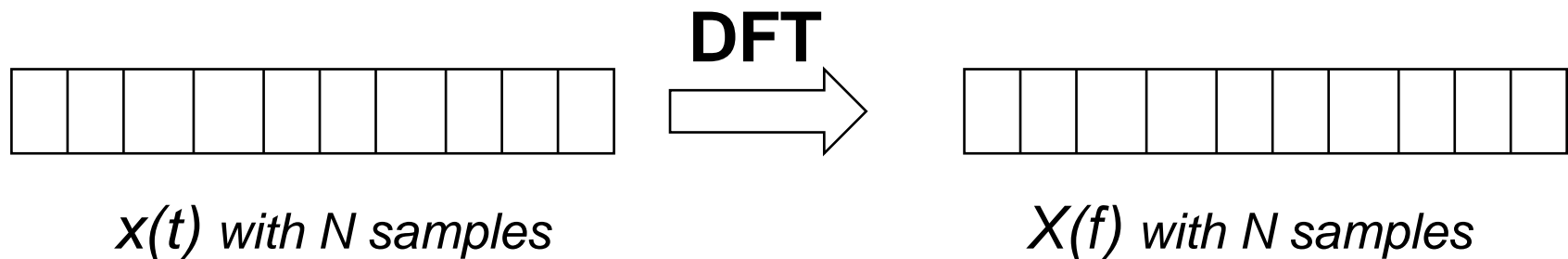


But we also talk about Continuous  
fourier transform (CFT) and discrete FT.



## Discrete Fourier Transform

DFT comes from CFT, but computed for some specific values:

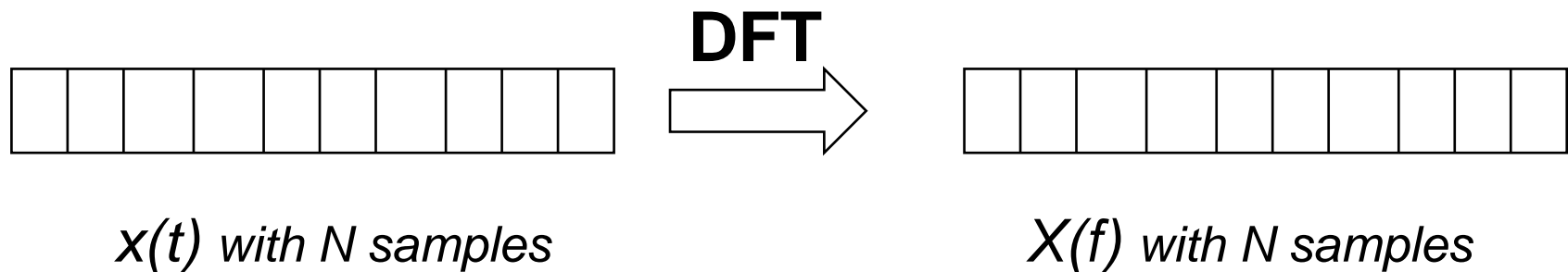


Thus same number of samples at the output: **NON REDUDANT**

CFT can be computed for any  $f$  value

$$X(f) = \int_{-\infty}^{+\infty} x(t) \cdot e^{-j2\pi f t} dt$$

## Discrete Fourier Transform



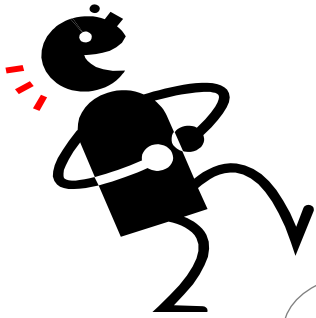
In **DFT** we choose only  **$N$**  frequency values that are equispaced so that the transformation is invertible.

DFT = special version of CFT that is non redundant and invertible

# Discrete Wavelet Transform (DWT)

DFT and CFT

Why CWT and DWT?



CWT: Any value of  $a$  and  $b$ .  
DWT: **Choose only values so that non redundant and invetible.**  
DFT: 1-D, but DWT: 2-D

## Series expansions

$$f(t) = \sum_{i=-\infty}^{+\infty} \alpha_i \cdot \phi_i(t)$$

The set of functions  $\{\phi_i(t)\}$ , with  $i \in R$ , are bases for  $f(t)$ .

$$f(t) \in L^2$$

**Orthonormality:** Orthogonal and unitary energy

$$\langle \phi_i(t), \phi_j(t) \rangle = \begin{cases} 0, & i \neq j \\ 1, & i = j \end{cases}$$

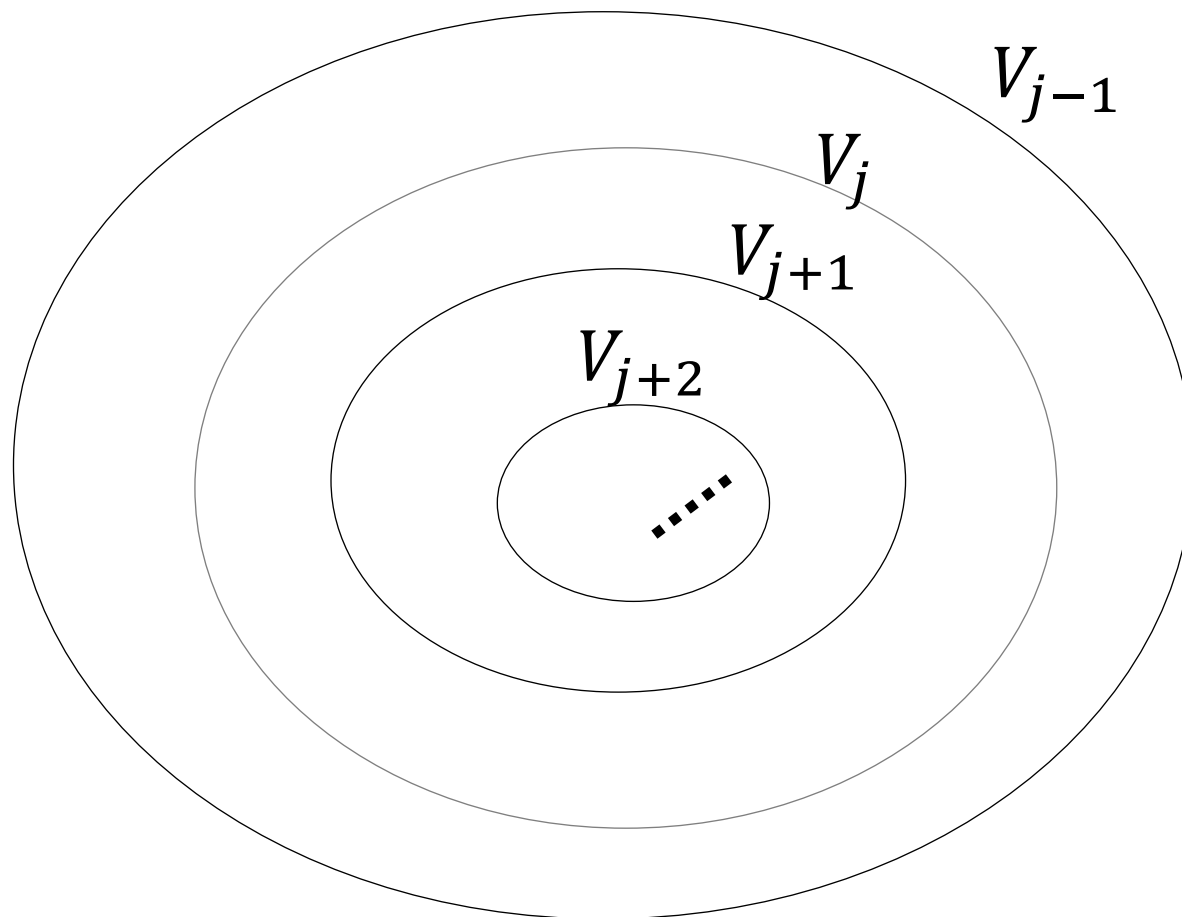
## Series expansions

$$f(t) = \sum_{i=-\infty}^{+\infty} \alpha_i \cdot \phi_i(t)$$

How to compute  $\alpha_i$  ?

$$\alpha_j = \langle f(t), \phi_j(t) \rangle$$

# MultiResolution Analysis (MRA)





## MRA properties

1)  $\dots \subset V_{j+2} \subset V_{j+1} \subset V_j \subset V_{j-1} \subset \dots$

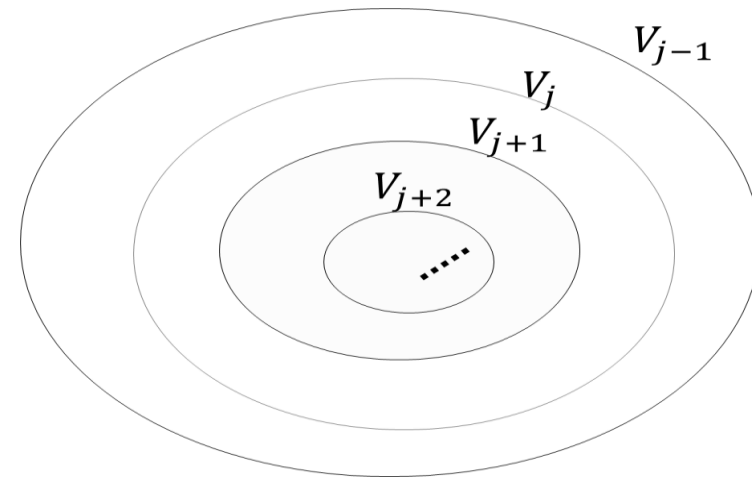
2)  $\lim_{j \rightarrow +\infty} V_j = \{\emptyset\}$

3)  $\lim_{j \rightarrow -\infty} V_j = L^2$

4) If  $f(t) \in V_0$  then  $f(t - n) \in V_0$  for  $n \in \mathbb{R}$

5) If  $f(t) \in V_j$  then  $f\left(\frac{t}{2}\right) \in V_{j+1}$

6)  $\{\theta(t - n)\}$  are orthonormal bases for  $V_0$



## MRA properties

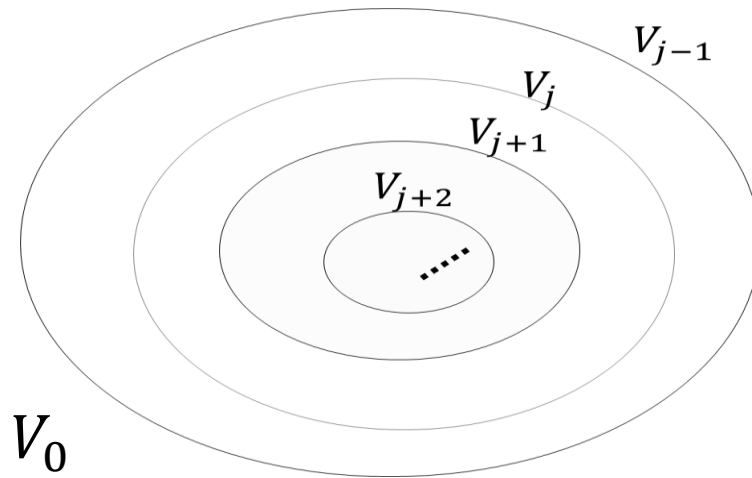
5) If  $f(t) \in V_j$  then  $f\left(\frac{t}{2}\right) \in V_{j+1}$

6)  $\{\theta(t - n)\}$  are orthonormal bases for  $V_0$

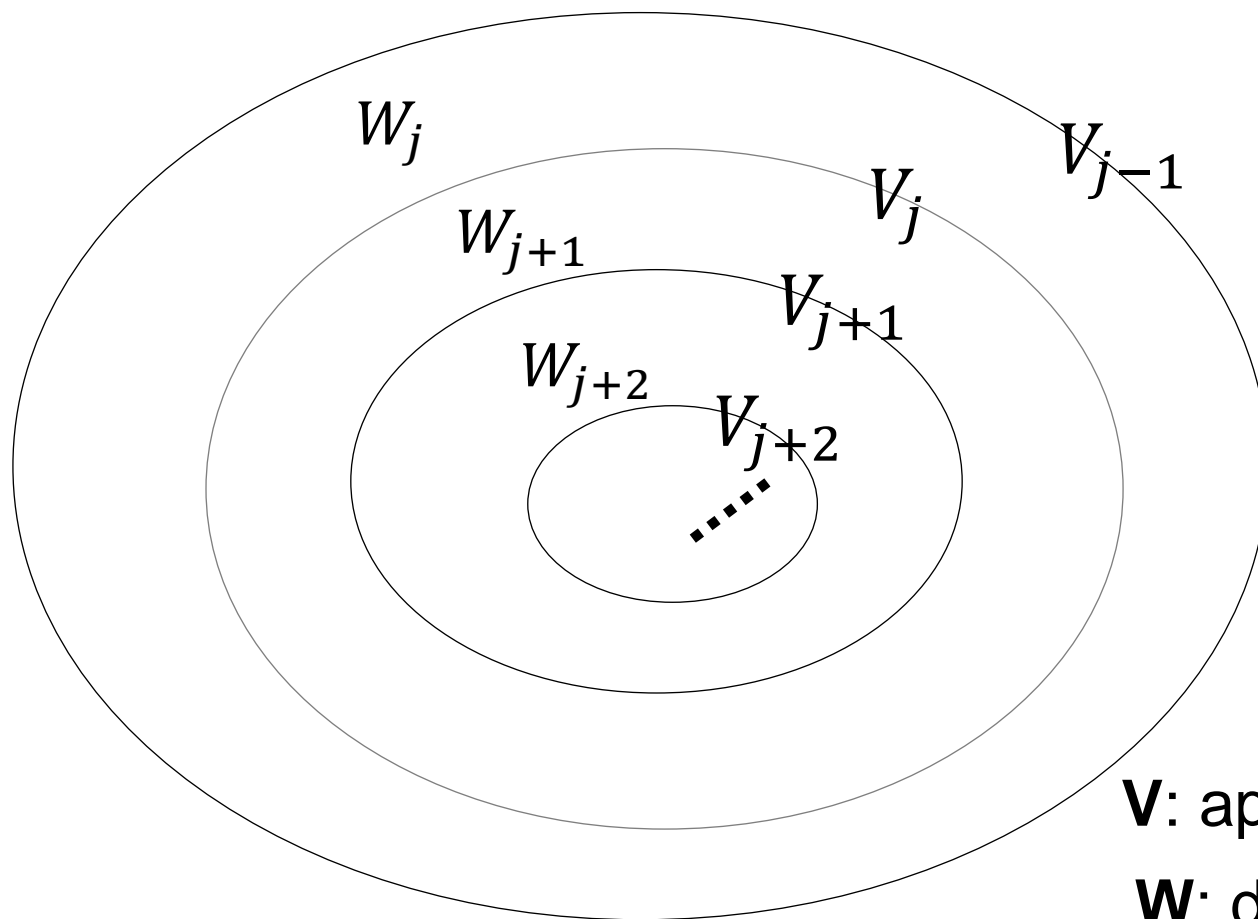
Combining properties (5) and (6) we have

$\left\{2^{-\frac{j}{2}} \cdot \theta(2^{-j}t - n)\right\}$  as orthonormal bases for  $V_j$

**$\theta(t)$  is called Scaling function**



## Approximation and detail spaces



**V**: approximation space

**W**: detail space

## Approximation and detail spaces

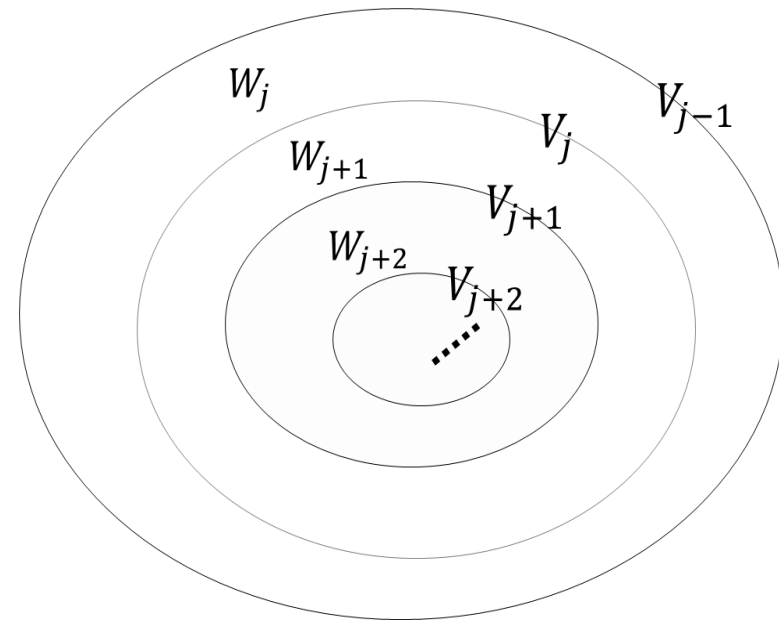
$$\begin{aligned}
 V_{j-1} &= V_j \oplus W_j \\
 &= V_{j+1} \oplus W_{j+1} \oplus W_j \\
 &= V_{j+2} \oplus W_{j+2} \oplus W_{j+1} \oplus W_j
 \end{aligned}$$

$$V_{j-1} = \bigcup_{k=0}^{+\infty} W_{j+k}$$

Thus  $L^2 = \bigcup_{j=-\infty}^{+\infty} W_j$

$\left\{ 2^{-\frac{j}{2}} \cdot \psi(2^{-j}t - n) \right\}$  as orthonormal bases for  $W_j$

**$\psi(t)$  is called wavelet function**



## Two scale equations

Relationship between 2 scales

$$\theta(t) = \sum_{n=-\infty}^{+\infty} h_n \cdot \sqrt{2} \theta(2t - n)$$

$$\psi(t) = \sum_{n=-\infty}^{+\infty} g_n \cdot \sqrt{2} \theta(2t - n)$$

$\langle \theta(t - n), \psi(t - m) \rangle = 0$ , *Orthogonal*

Example: MRA of  $f(t)$

## Exercises

### Questions and Answers

**Part I:** Each group will come up with 2 questions on CWT. I will pick one member to read the questions for the audience. Each project will work on the answers during the exercises time.

### What did you not understand?

**Part II:** Each group will come up with 2 questions on DWT.  
(30 minutes)

# Group Work (45 minutes)

