

Problem 2 Overview A: Intro to wavelets

1. A quick reminder on Fourier series..... with sines and cosines

Consider an *semi-even* target function $f(x)$ in Figure 1 (Note: This function will be properly even if you subtract the DC offset value from $f(x)$).

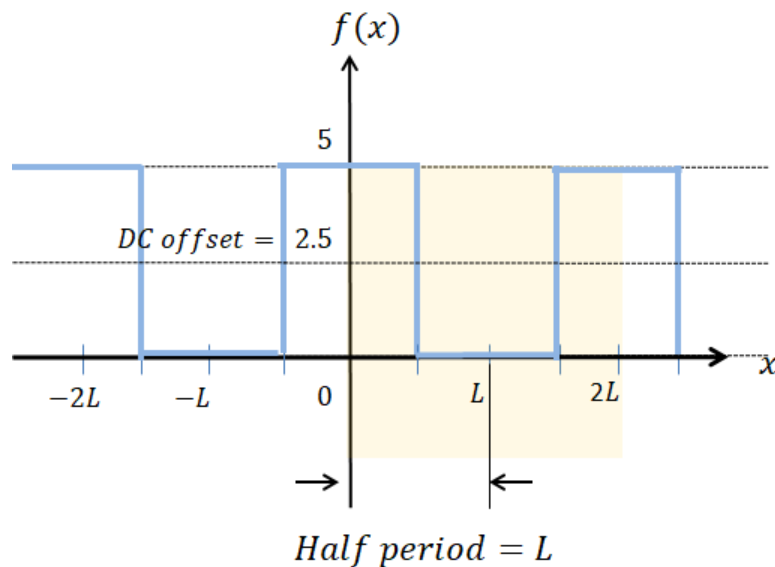
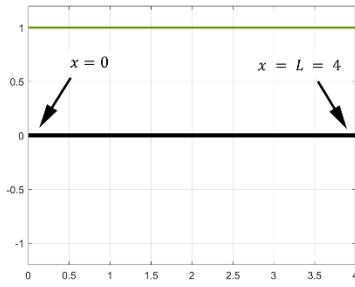


Figure 1: The target function $f(x)$ can be reconstructed using a linear combination of cosines !

In the previous homework set, you know that $f(x)$ can be best approximated by taking linear combinations of sines and cosines (with $m = 0$ being the DC offset component):

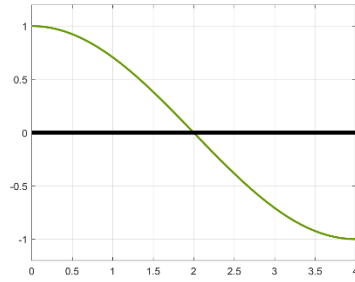
$$\left\{ \begin{array}{l} \text{Target: } f(x) = a_0 \psi_0(x) + a_1 \psi_1(x) + a_2 \psi_2(x) + \cdots + a_m \psi_m(x) \\ \quad \quad \quad + b_1 \phi_1(x) + b_2 \phi_2(x) + \cdots + b_n \phi_n(x) \\ \\ \text{Basis set: } \psi_m(x) = \left\{ \cos\left(\frac{m\pi}{L}x\right) \right\}, \text{ where } m = 0, 1, 2, \dots \text{ positive integers} \\ \quad \quad \quad \phi_m(x) = \left\{ \sin\left(\frac{n\pi}{L}x\right) \right\}, \text{ where } n = 1, 2, \dots \text{ positive integers} \end{array} \right.$$



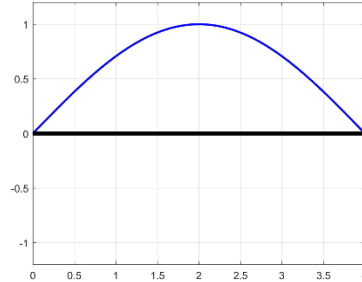
$$\psi_0 = 1$$

$$m = 0$$

Lowest frequency basis
(global DC average)



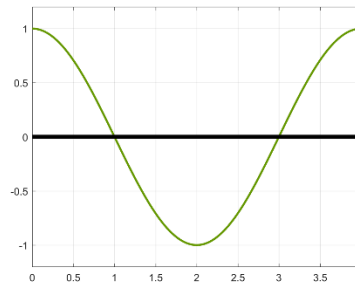
$$\psi_1 = \cos\left(\frac{\pi}{L}x\right)$$



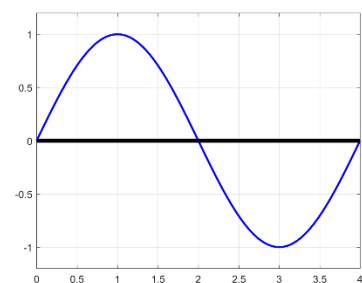
$$\phi_1 = \sin\left(\frac{\pi}{L}x\right)$$

$$m, n = 1$$

"Really rough" spatial
frequency basis



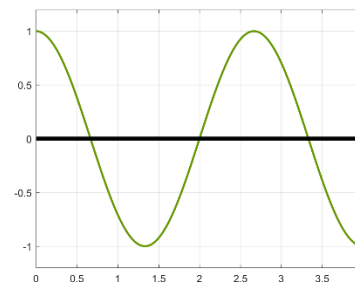
$$\psi_2 = \cos\left(\frac{2\pi}{L}x\right)$$



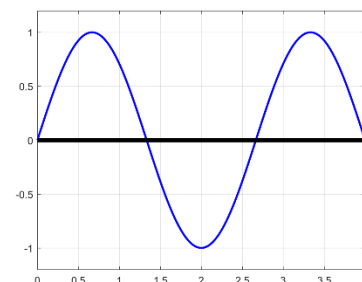
$$\phi_2 = \sin\left(\frac{2\pi}{L}x\right)$$

$$m, n = 2$$

"Coarse" spatial
frequency basis



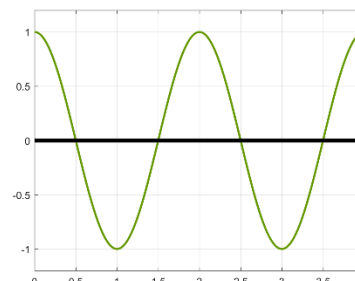
$$\psi_3 = \cos\left(\frac{3\pi}{L}x\right)$$



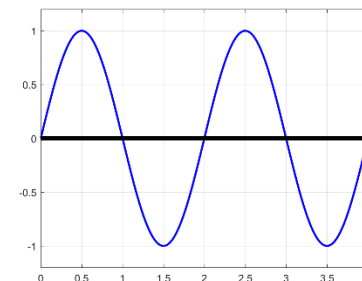
$$\phi_3 = \sin\left(\frac{3\pi}{L}x\right)$$

$$m, n = 3$$

"Medium" spatial
frequency basis



$$\psi_4 = \cos\left(\frac{4\pi}{L}x\right)$$



$$\phi_4 = \sin\left(\frac{4\pi}{L}x\right)$$

$$m, n = 4$$

"Fine" spatial
frequency basis

Figure 2:

The $(m = 0)$ basis can be used to approximate the global average value of our target function $f(x)$, while the higher-frequency basis at $(m, n = 3)$ will be used to capture fine details within $f(x)$

Suppose our *half period* for $f(x)$ in Figure 1 was $L = 4$. If you examine Figure 2, we see that the as the values of m and n increase, our Fourier reconstruction of $f(x)$ will be more and more accurate. This is because at high m, n -values, the spatial frequencies of the sine / cosine basis functions will be able to capture finer and finer details of $f(x)$.

A corollary statement of the above paragraph would be:

If you can figure out how many basis terms you can throw away while still retaining a good approximation to $f(x)$, you can drastically save computational time and memory in your reconstruction of $f(x)$!!!

This begs the question: How many c 's can we throw out (In other words, how many of these c 's can we set to zero ?)

$$f(x) = a_0 \psi_0(x) + a_1 \psi_1(x) + a_2 \psi_2(x) + \cancel{a_3 \psi_3(x)} + \cancel{a_4 \psi_4(x)} + \dots + \cancel{a_m \psi_m(x)} \\ + \cancel{b_1 \phi_1(x)} + \cancel{b_2 \phi_2(x)} + \dots + \cancel{b_n \phi_n(x)}$$

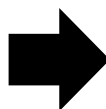


Filter out unnecessary Fourier coefficients

Good enough for $f(x)$ reconstruction



Saves memory + computation time !!



This is the essence of **data compression** !...
and this is where wavelets are useful in engineering !

2. The wavelet basis \approx Cosines + sines on steroids !

Once you're comfortable with the concepts of orthogonal basis, Fourier coefficients, and change of basis (the Lecture #8 material involving $Qc = Ib$, $Q^{-1}AQc = b$, and $Ac = Sb$), you will have no problem understanding how digital wavelets work. Why ? This is because:

Digital wavelet basis vectors = orthogonal basis sets (can be normalized if necessary)
 \approx *Essentially a digital cousin of cosines and sines !*

Ok – let's start ! Suppose we know the values within a **4-point segment** of some **digitized** function $f(x)$ depicted in Figure 4:

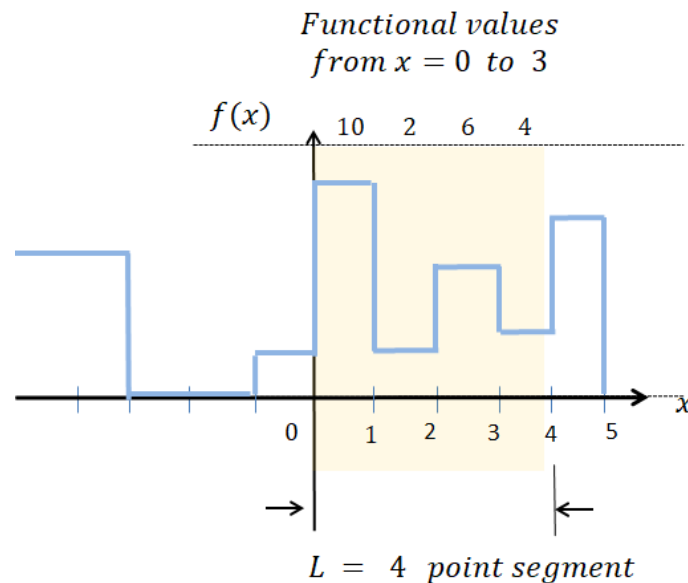


Figure 4: A 4-point segment of a *non-even, non-odd, non-periodic* digital function $f(x)$

The first couple things to notice are:

- The function $f(x)$ does not have to be periodic
- $f(x)$ exhibits neither odd nor even symmetry
- The functional values 10, 2, 6, 3 were sampled from the left edge of each histogram bar. In other words, our 4-point segment can be written as a target vector b :

$$\text{Target vector: } b = \begin{bmatrix} f(0) \\ f(1) \\ f(2) \\ f(3) \end{bmatrix} = \begin{bmatrix} 10 \\ 2 \\ 6 \\ 4 \end{bmatrix}$$

2a) The “4-point Haar wavelet” basis set: The Fourier series perspective

Just like Fourier series, the quintessential question here is: Can we reconstruct our target digital sample (vector b) as a finite linear combination of some digital basis vectors $\overrightarrow{w_n}$?

$$\left\{ \begin{array}{l} \text{Target:} \quad b = c_0 \overrightarrow{w_0} + c_1 \overrightarrow{w_1} + c_2 \overrightarrow{w_2} + c_3 \overrightarrow{w_3} \\ \text{Basis set:} \quad \overrightarrow{w_n}, \quad \text{where } n = 0, 1, 2, 3 \end{array} \right.$$

In this homework problem, we will explore using the “4-point Haar basis” set denoted by matrix W :

$$W = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & -1 & 0 \\ 1 & -1 & 0 & 1 \\ 1 & -1 & 0 & -1 \end{bmatrix} \rightarrow \begin{array}{l} \text{Orthogonal column vectors} \\ \text{(but not normal !)} \end{array}$$

$\overrightarrow{w_0} \quad \overrightarrow{w_1} \quad \overrightarrow{w_2} \quad \overrightarrow{w_3}$

Like all good orthogonal basis sets, they must obey a certain set of orthogonality and (norm)² rules !

$$\langle \overrightarrow{w_p}, \overrightarrow{w_q} \rangle = \overrightarrow{w_p} \cdot \overrightarrow{w_q} = \begin{cases} 0 & \text{if } p \neq q \quad (\text{orthogonality}) \\ \begin{matrix} \|\overrightarrow{w_0}\|^2 = 4 & \|\overrightarrow{w_2}\|^2 = 2 \\ \|\overrightarrow{w_1}\|^2 = 4 & \|\overrightarrow{w_3}\|^2 = 2 \end{matrix} & \text{if } p = q \quad (\text{norm})^2 \end{cases}$$

Hmmm..... this suggests the Haar wavelet coefficients c_n are also *generalized Fourier coefficients !!* \Rightarrow Hence, we can easily find these coefficients by applying inner products ! Given:

Target vector reconstruction : $\vec{b} = c_0 \overrightarrow{w_0} + \dots + c_n \overrightarrow{w_n}, \quad \text{where } n = 0, 1, 2, 3$

Invoking inner products and orthogonality with respect to $\overrightarrow{w_n}$:

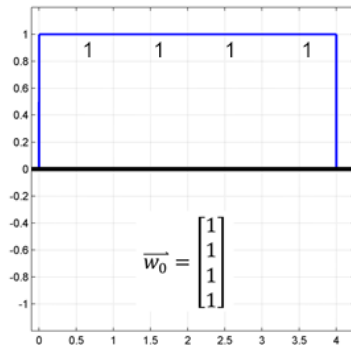
$$\langle \vec{b}, \overrightarrow{w_n} \rangle = c_0 \underbrace{\langle \overrightarrow{w_0}, \overrightarrow{w_n} \rangle}_0 + c_1 \underbrace{\langle \overrightarrow{w_1}, \overrightarrow{w_n} \rangle}_0 + \dots + c_n \underbrace{\langle \overrightarrow{w_n}, \overrightarrow{w_n} \rangle}_{(\text{norm})^2}$$

We can easily solve for c_n :

$$c_n = \frac{\langle \vec{b}, \overrightarrow{w_n} \rangle}{\langle \overrightarrow{w_n}, \overrightarrow{w_n} \rangle} = \frac{\vec{b} \cdot \overrightarrow{w_n}}{(\text{norm})^2} = \frac{b^T w_n}{(\text{norm})^2}$$

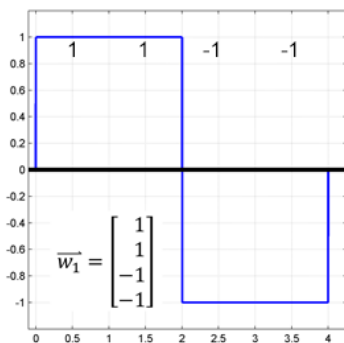
2b) The Haar wavelet basis set: A multi-scale mixture of cosines and sines!

Similar to what we've done in Figure 2 for the cosine basis, let's plot the Haar wavelet basis set against the backdrop of our data axis x with a data word length of $L = 4$ in Figure 5:



$J = 0$

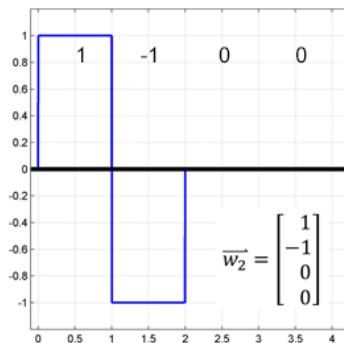
Lowest frequency basis
(DC value)



$J = 1$

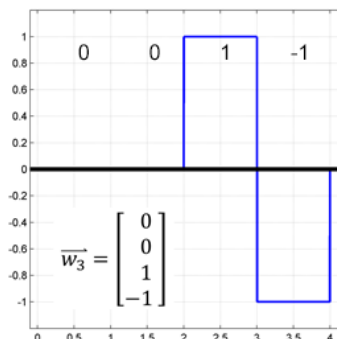
"Coarse" basis
(digital sine)

Wave compression !!



$J = 2$

"Fine" basis
(digital sines @ higher frequencies)



$\vec{w}_2 = 2x$ the spatial
frequency of \vec{w}_1

$\vec{w}_3 =$ Shifted version of \vec{w}_2

Figure 5: The 4-point Haar wavelet bases \vec{w}_n look just like digital sines and cosines at different roughness scales.

After a quick peek at Figure 4, you might be thinking: *Wait a minute.... these digital square pulses kind of look like:*

i) The \vec{w}_0 wavelet \leftrightarrow Similar to the cosine DC basis : $\cos\left(\frac{2^J \pi}{L} x\right)$, with $J = 0$

ii) The \vec{w}_1 wavelet \leftrightarrow Analogous to a coarse sine basis : $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 1$

iii) The \vec{w}_2 wavelet \leftrightarrow $2x$ – compressed version of $J = 1$: $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 2$

iv) The \vec{w}_3 wavelet \leftrightarrow A shifted version of of the above : $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 2$
where:

$J =$ 'The granularity' (or the level of roughness) of the spatial frequency of each set of basis vectors

$=$ The spatial frequency will double for an unit increase in J – level

Hence, the 4-point Haar wavelets basis are essentially distant digital cousins of the sines and cosines bases used in Fourier series !! And again, the best part about the basis set \vec{w}_n is that they obey a set of orthogonality and (norm)² relationships !

2c) You can “build” larger Haar wavelet basis sets for longer data word length !

Suppose we extend our data word length such that $L = 8$. If we were going to reconstruct the yellow-shaded target data in Figure 6, we must expand our wavelet basis set in a way in which:

- 1) Our new Haar matrix W is an 8×8 matrix
- 2) Our new basis set \vec{w}_n will be able to reconstruct “super-fine” details within our target data
- 3) Our new basis set \vec{w}_n must contain a larger selection of “coarse” and “fine” spatial frequency basis vectors for us to choose from.

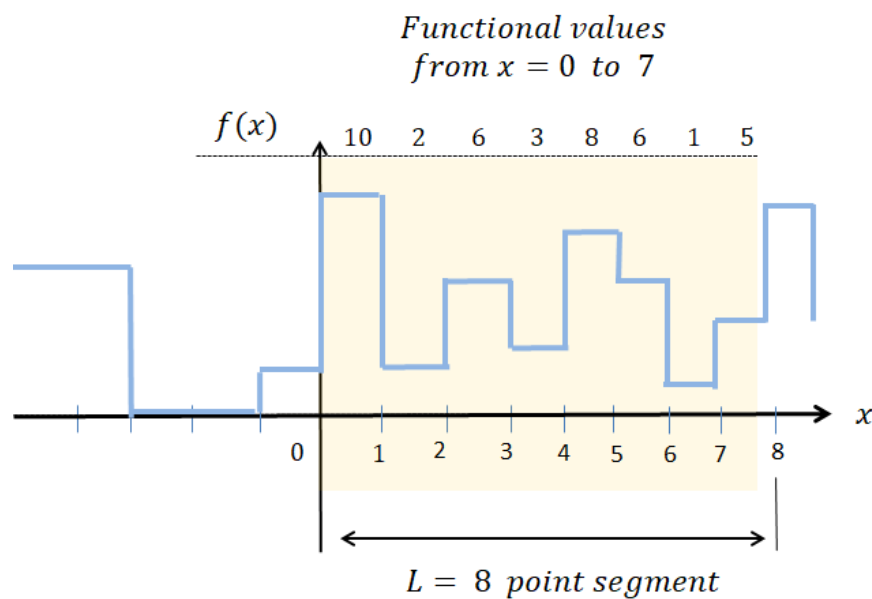
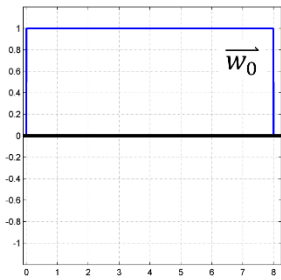


Figure 6: If we extend our “data word length” to 8 data entries, we also need to expand our Haar basis set to accommodate for the longer target vector.

Now, to accommodate an $b = \mathbb{R}^8$ target vector, we shall extend our 4-point Haar basis set by increasing the spatial frequency by 2 (such that we’ll get 8 total basis vectors). The new basis set are depicted in Figure 7.

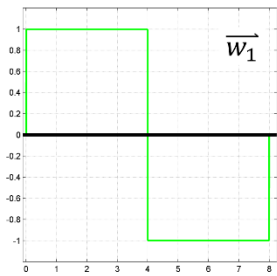
$$\text{Longer target vector: } b = \begin{bmatrix} f(0) \\ f(1) \\ f(2) \\ f(3) \\ f(4) \\ f(5) \\ f(6) \\ f(7) \end{bmatrix} = \begin{bmatrix} 10 \\ 2 \\ 6 \\ 3 \\ 8 \\ 6 \\ 1 \\ 5 \end{bmatrix}$$

Figure 7: The 8-point Haar basis set



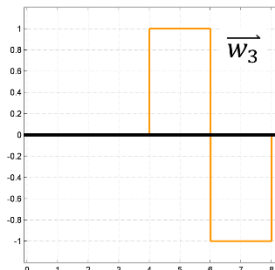
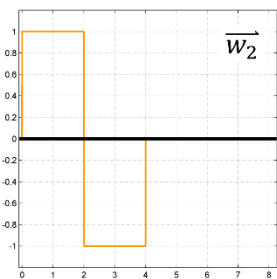
$J = 0$

Lowest spatial
freq basis
(global DC average)



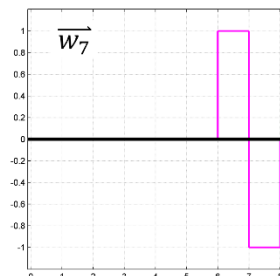
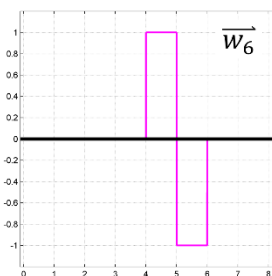
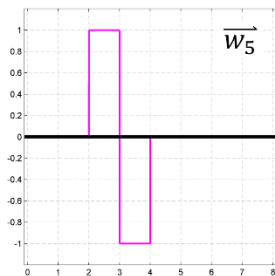
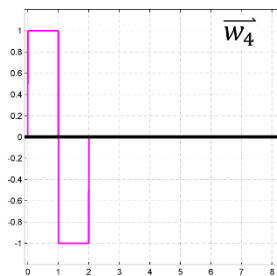
$J = 1$

Coarse basis
(digital sine)



$J = 2$

Fine basis
(2x freq of $J = 1$)



$J = 3$

Super-fine basis
(4x freq of $J = 1$)

$$W = \begin{bmatrix} \begin{matrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{matrix} & \begin{matrix} 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \end{matrix} & \begin{matrix} 1 & 0 & -1 & 0 & -1 & 0 & 0 & 1 \end{matrix} & \begin{matrix} 0 & 0 & 0 & 0 & 1 & 1 & -1 & -1 \end{matrix} & \begin{matrix} 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 1 & -1 & 0 & 0 & -1 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 0 & 1 & 0 & -1 & 0 & 1 \end{matrix} & \begin{matrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{matrix} \end{bmatrix}$$

\vec{w}_0 \vec{w}_1 \vec{w}_2 \vec{w}_3 \vec{w}_4 \vec{w}_5 \vec{w}_6 \vec{w}_7

Just like the 4-point Haar basis set, the 8-point basis set also exhibits the special property: An unit increase in the J -level causes a 2x increase in spatial frequency in the basis vectors.

i) $\vec{w}_0 \leftrightarrow$ Similar to the cosine DC basis : $\cos\left(\frac{2^J \pi}{L} x\right)$, with $J = 0$

ii) $\vec{w}_1 \leftrightarrow$ Analogous to a coarse sine basis : $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 1$

iii) $\vec{w}_2 \leftrightarrow$ 2x – compressed version of $J = 1$: $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 2$

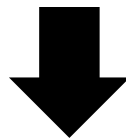
iv) $\vec{w}_3 \leftrightarrow$ A shifted version of of the above : $\sin\left(\frac{2^J \pi}{L} x\right)$

v) $\vec{w}_4 \leftrightarrow$ 2x – compressed version of $J = 2$: $\sin\left(\frac{2^J \pi}{L} x\right)$, with $J = 3$

vi) $\vec{w}_5 \leftrightarrow$ A shifted version of of the above : $\sin\left(\frac{2^J \pi}{L} x\right)$

vii) $\vec{w}_6 \leftrightarrow$ A shifted version of of the above : $\sin\left(\frac{2^J \pi}{L} x\right)$

viii) $\vec{w}_7 \leftrightarrow$ A shifted version of of the above : $\sin\left(\frac{2^J \pi}{L} x\right)$



This immediately suggests we can build a Haar matrix that can accommodate any target data sets with a word length of 2^J !! =)

To reconstruct a target vector
with a word length of $L = 2^J$

- {
1. Extend the Haar basis set to J – levels
 2. Within each level, you will have 2^{J-1} total basis members containing equally – spaced shifts within the interval $[0, L]$