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Digital Signal Processing

Module 3: from Euclid to Hilbert

- ▶ **Module 3.1:** Signal processing as geometry or from Euclid to Hilbert spaces
- ▶ **Module 3.2:** Vectors, vector spaces, inner products, and Hilbert spaces
- ▶ **Module 3.3:** Bases for Hilbert spaces

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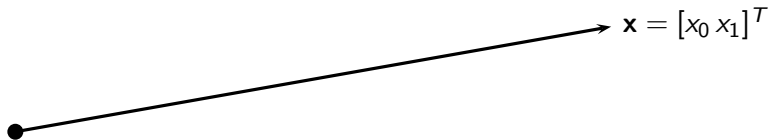
Module 3.1: a tale of two (and more) vectors

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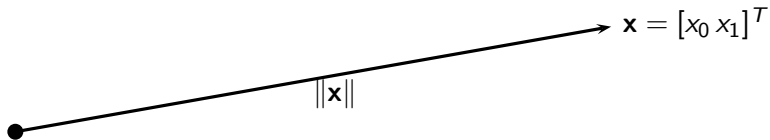
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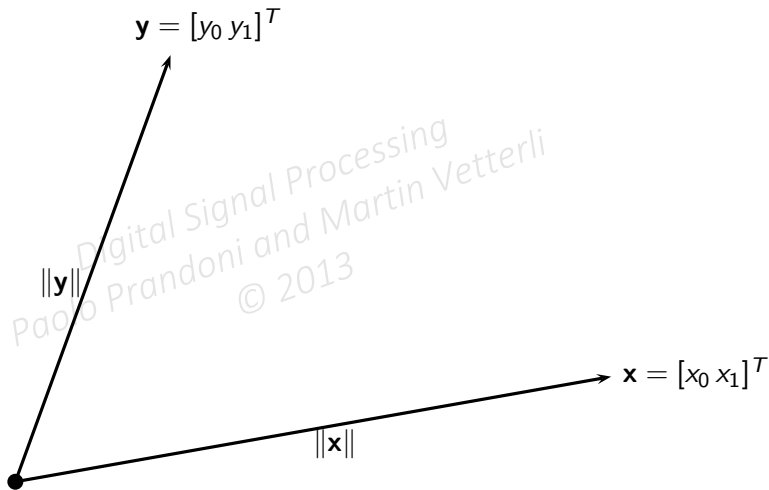


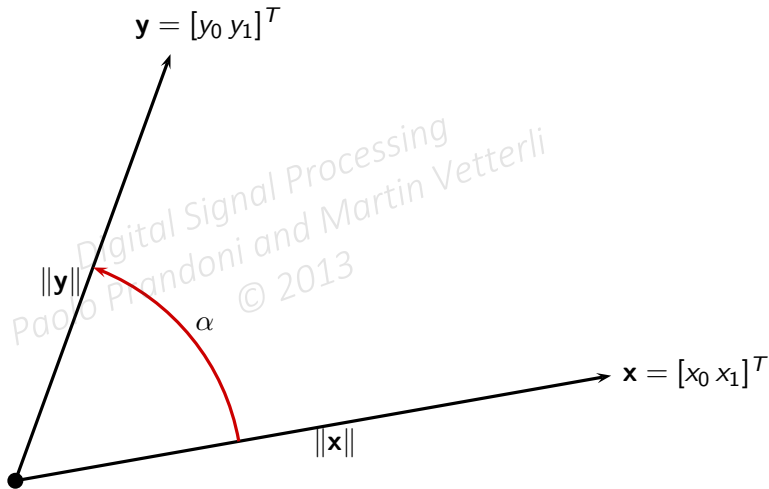
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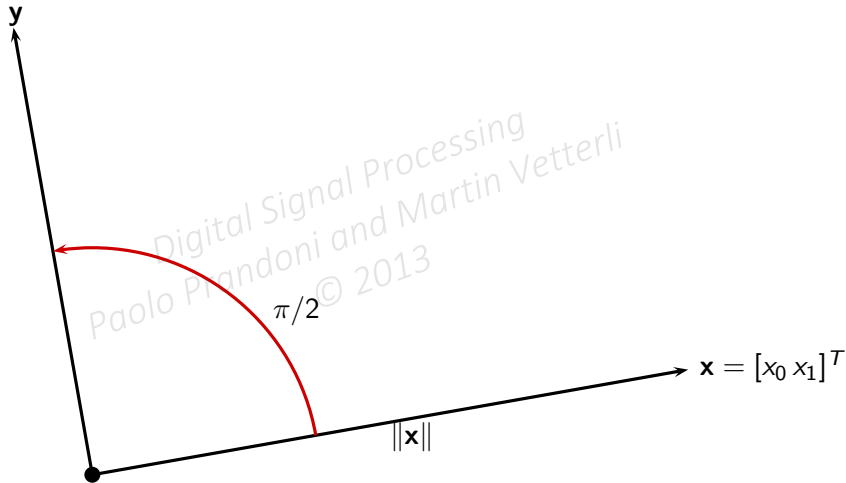


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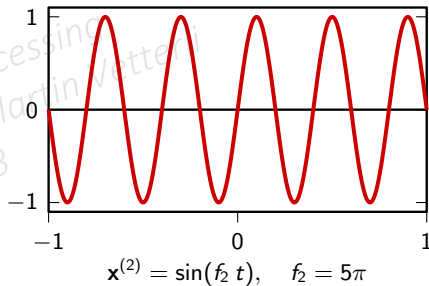
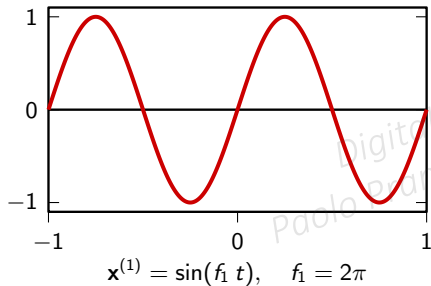






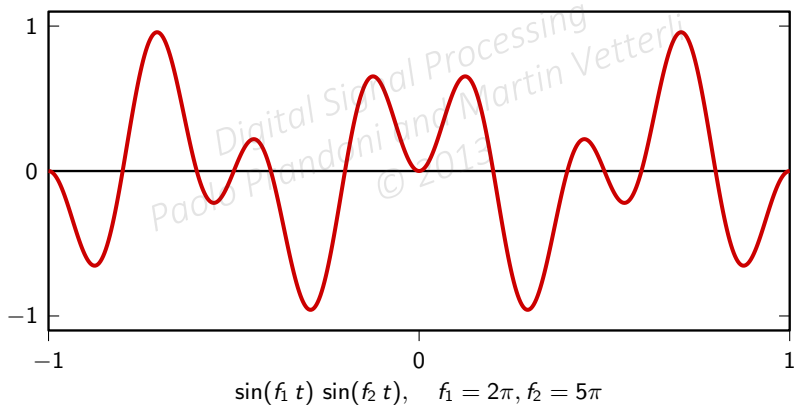
Vectors can be very general objects!

Example: space of square-integrable functions over $[-1, 1]$: $L_2([-1, 1])$

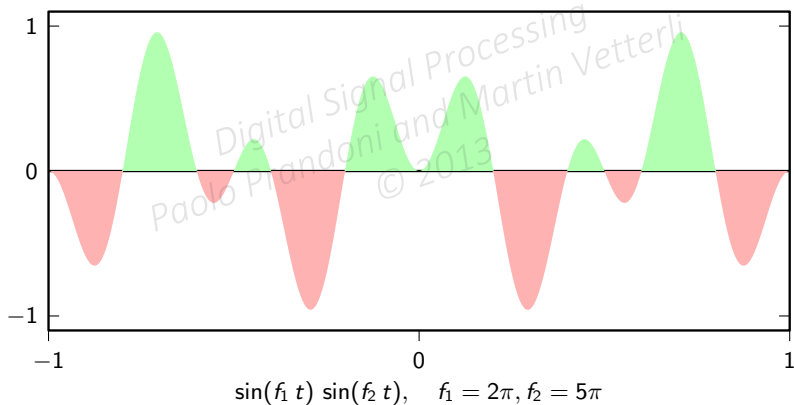


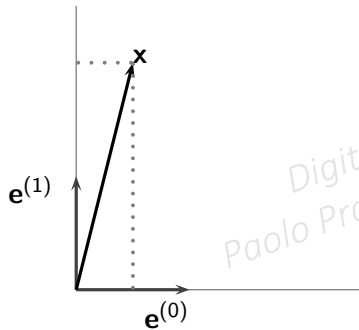
$$\langle \mathbf{x}^{(1)}, \mathbf{x}^{(2)} \rangle = \int_{-1}^1 \sin(f_1 t) \sin(f_2 t) dt$$

$\mathbf{x}^{(1)} \perp \mathbf{x}^{(2)}$ if $f_1 \neq f_2$ and f_1, f_2 integer multiples of a fundamental (harmonically related)

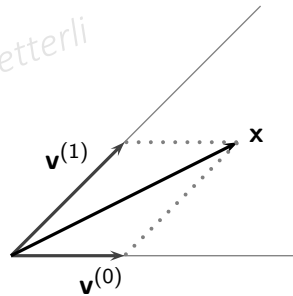


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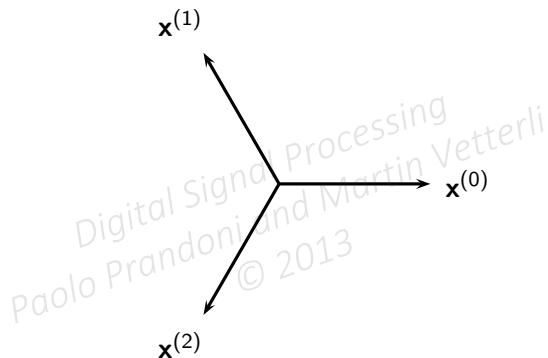


orthogonal basis



biorthogonal basis

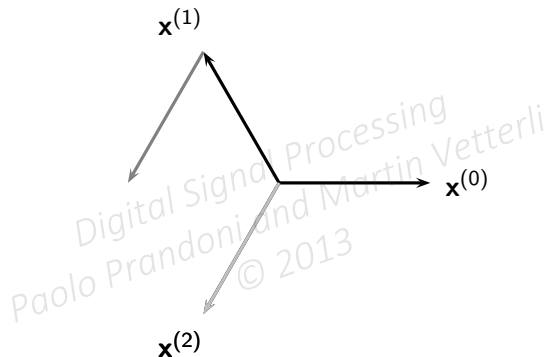
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Linear dependence:

$$\exists \{a_0, a_1, a_2\} \text{ s.t. } a_0 \mathbf{x}^{(0)} + a_1 \mathbf{x}^{(1)} + a_2 \mathbf{x}^{(2)} = 0$$

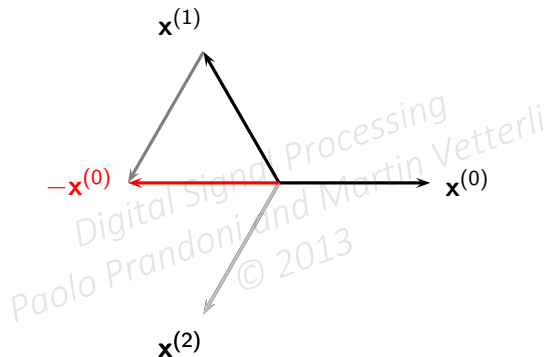
Too many vectors for the space



Linear dependence:

$$\exists \{a_0, a_1, a_2\} \text{ s.t. } a_0 \mathbf{x}^{(0)} + a_1 \mathbf{x}^{(1)} + a_2 \mathbf{x}^{(2)} = \mathbf{0}$$

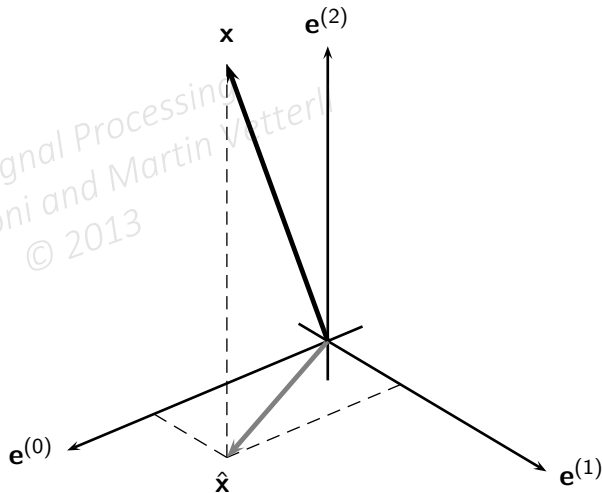
Too many vectors for the space



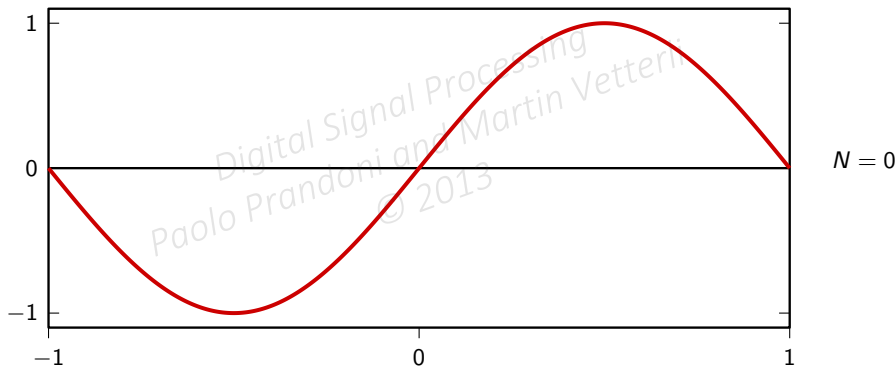
Linear dependence:

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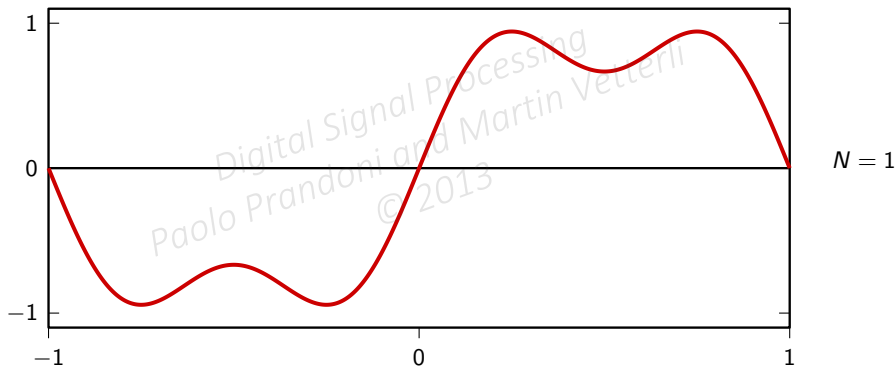
subspace projection: $\hat{\mathbf{x}}$ is the closest approximation to \mathbf{x} in the space spanned by $\{\mathbf{e}^{(0)}, \mathbf{e}^{(1)}\}$



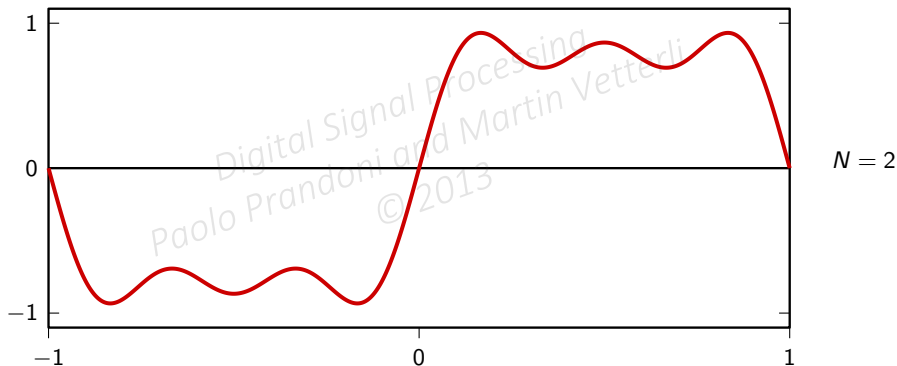
$$\sum_{k=0}^N \mathbf{x}^{(2k+1)}, \quad \mathbf{x}^{(n)} = \sin(\pi n t)/n, \quad t \in [-1, 1]$$



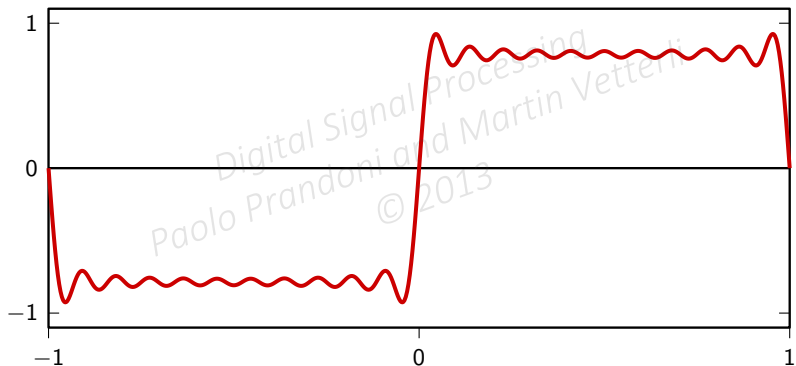
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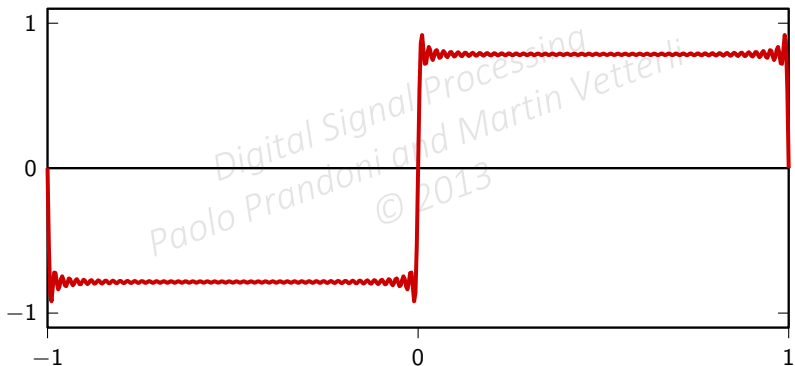


$$\sum_{k=0}^N \mathbf{x}^{(2k+1)}, \quad \mathbf{x}^{(n)} = \sin(\pi n t)/n, \quad t \in [-1, 1]$$



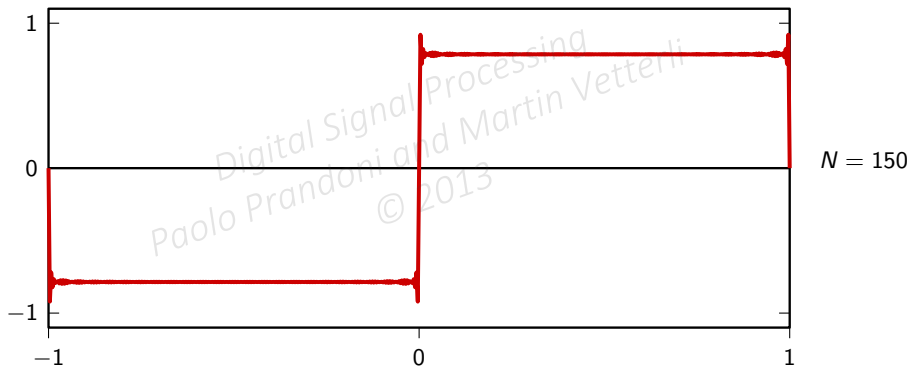
$N = 10$

$$\sum_{k=0}^N \mathbf{x}^{(2k+1)}, \quad \mathbf{x}^{(n)} = \sin(\pi n t)/n, \quad t \in [-1, 1]$$



$N = 50$

$$\sum_{k=0}^N \mathbf{x}^{(2k+1)}, \quad \mathbf{x}^{(n)} = \sin(\pi n t)/n, \quad t \in [-1, 1]$$



END OF MODULE 3.1

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Module 3.2: Hilbert Space, properties and bases

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- ▶ Definition of Hilbert space

- ▶ Examples

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- ▶ Definition of Hilbert space
- ▶ Examples

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1. a vector space: $H(V, \mathbb{C})$

2. an inner product: $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{C}$

3. completeness

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1) Vector space



We need *at least* to:

- ▶ resize vectors: scalar multiplication
- ▶ combine vectors together: addition

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1) Vector space



We need *at least* to:

- ▶ resize vectors: scalar multiplication
- ▶ combine vectors together: addition

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$$\mathbf{x} = [x_0 \ x_1]^T$$

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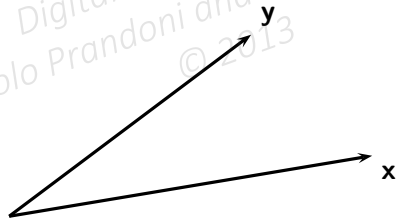
$$a\mathbf{x} = [ax_0 \quad ax_1]^T$$

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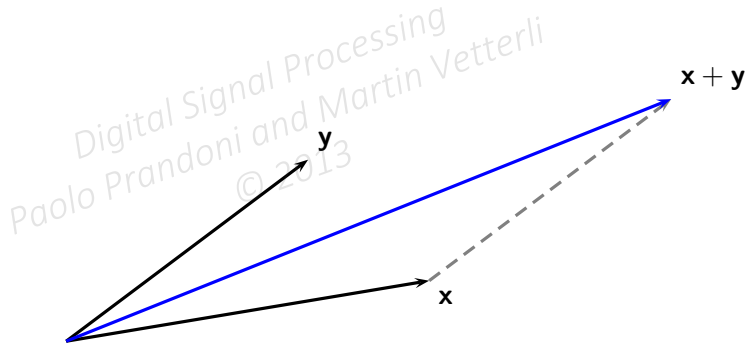


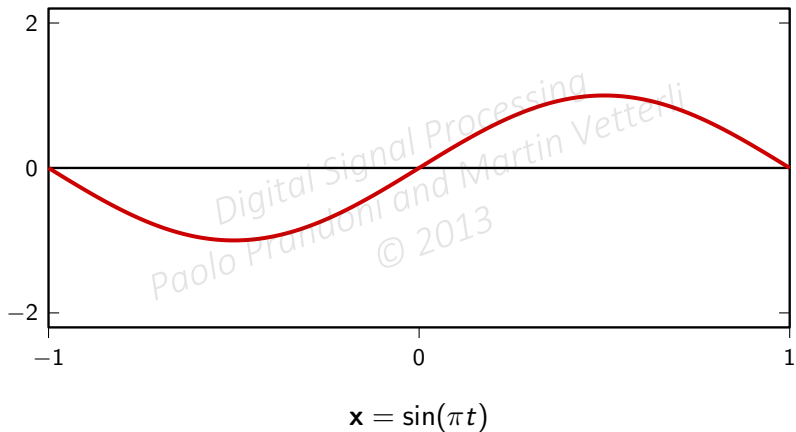
\mathbf{x}, \mathbf{y}

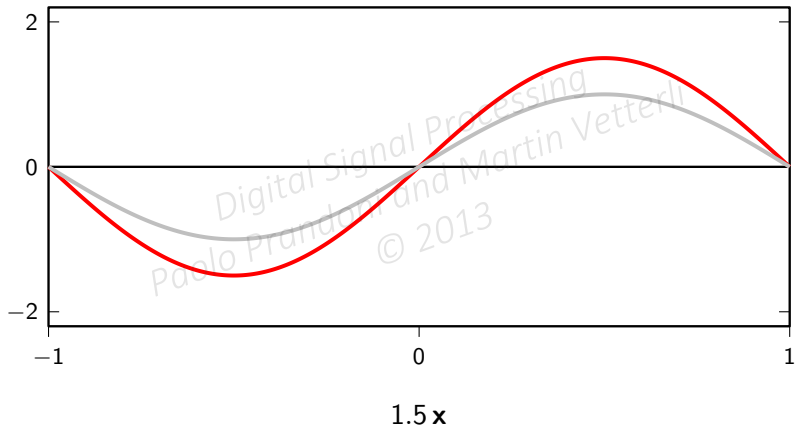
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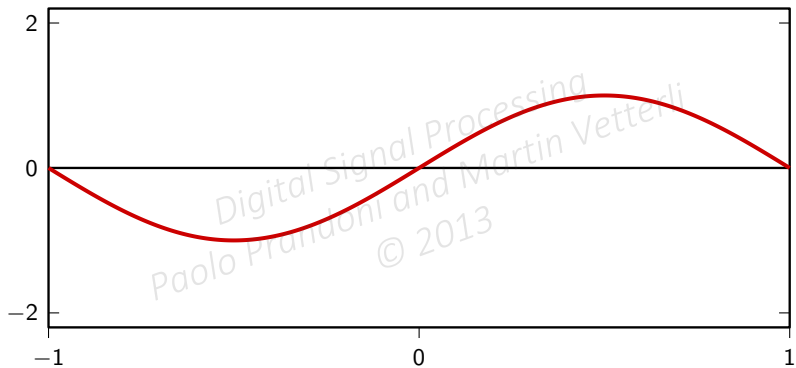


$$\mathbf{x} + \mathbf{y} = [x_0 + y_0 \quad x_1 + y_1]^T$$

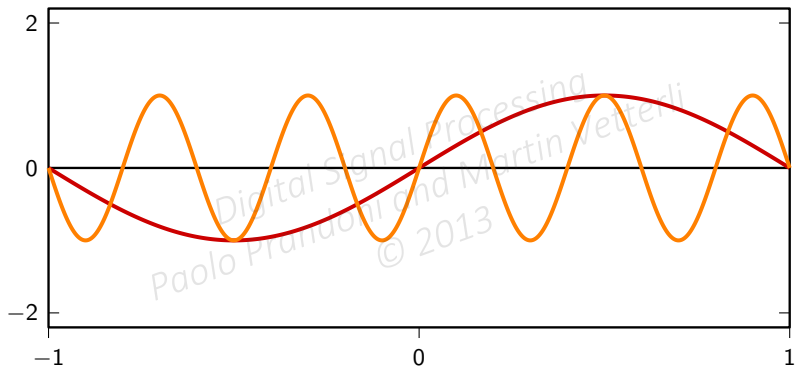




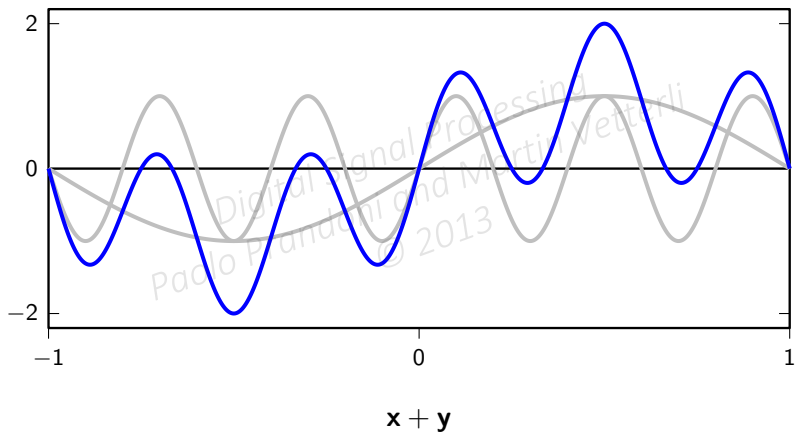




$$x = \sin(\pi t)$$



$$y = \sin(5\pi t)$$



For $\mathbf{x}, \mathbf{y}, \mathbf{z} \in V$ and $\alpha, \beta \in \mathbb{C}$:

► $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$

► $(\mathbf{x} + \mathbf{y}) + \mathbf{z} = \mathbf{x} + (\mathbf{y} + \mathbf{z})$

► $\alpha(\mathbf{x} + \mathbf{y}) = \alpha\mathbf{y} + \alpha\mathbf{x}$

► $(\alpha + \beta)\mathbf{x} = \alpha\mathbf{x} + \beta\mathbf{x}$

► $\alpha(\beta\mathbf{x}) = (\alpha\beta)\mathbf{x}$

► $\exists 0 \in V \quad | \quad \mathbf{x} + 0 = 0 + \mathbf{x} = \mathbf{x}$

► $\forall \mathbf{x} \in V \exists (-\mathbf{x}) \quad | \quad \mathbf{x} + (-\mathbf{x}) = 0$

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Formal properties of a vector space:

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- intuition: $\mathbb{R}^2 \subset \mathbb{R}^3$

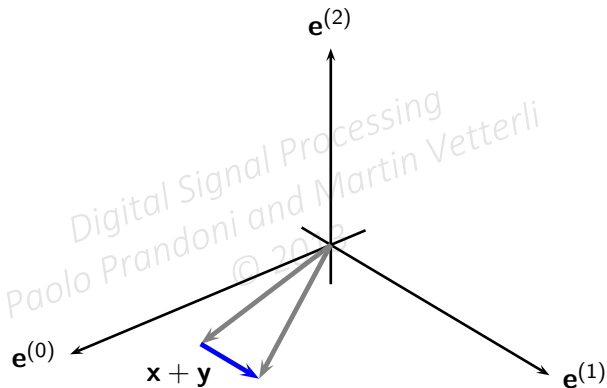
- addition and scaling in subspace remain in subspace

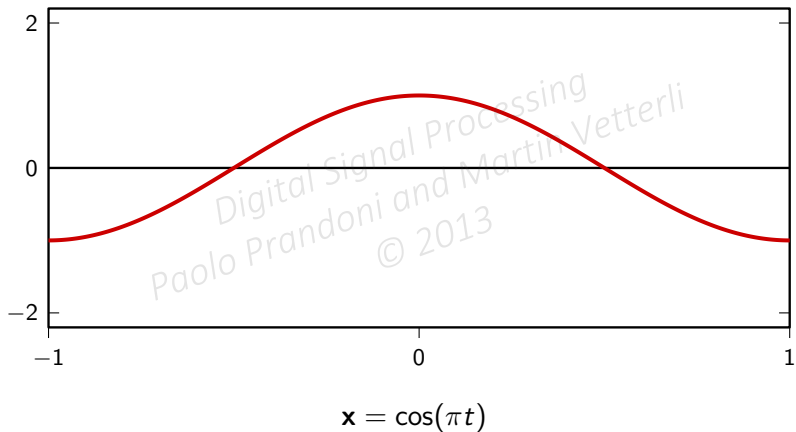
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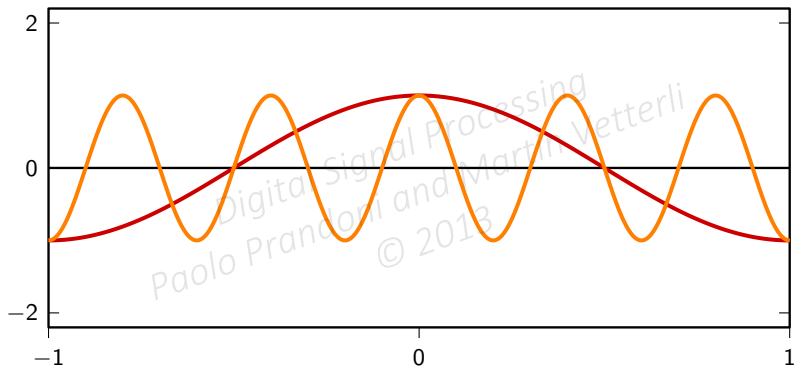
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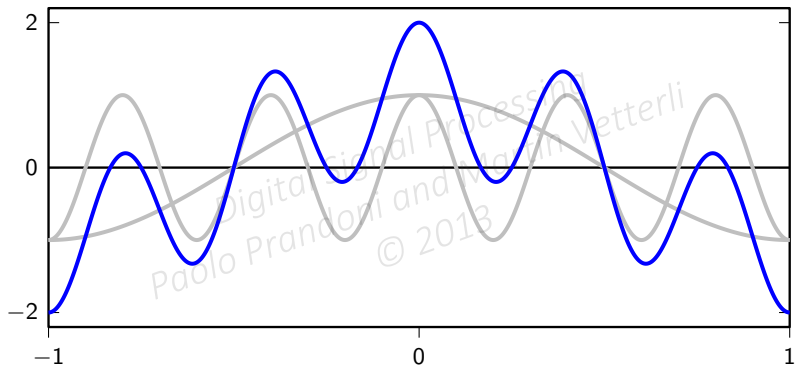
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$$y = \cos(5\pi t)$$



$x + y$, symmetric

2) Inner product



- ▶ **measure of similarity between vectors**
- ▶ when inner product is zero vectors are most different: orthogonal vectors

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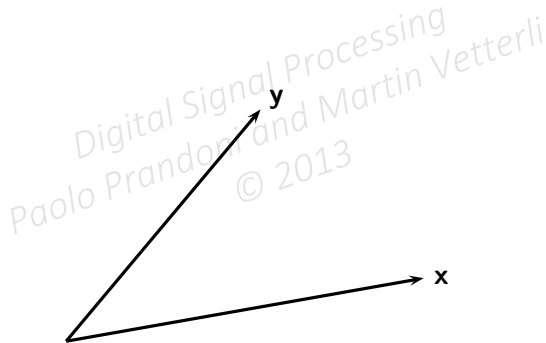
2) Inner product



- ▶ measure of similarity between vectors
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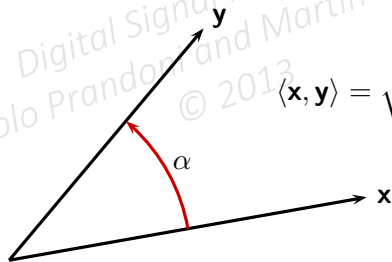
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$$\langle \mathbf{x}, \mathbf{y} \rangle = x_0 y_0 + x_1 y_1$$



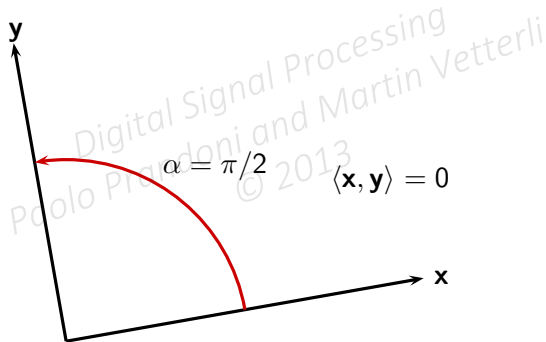
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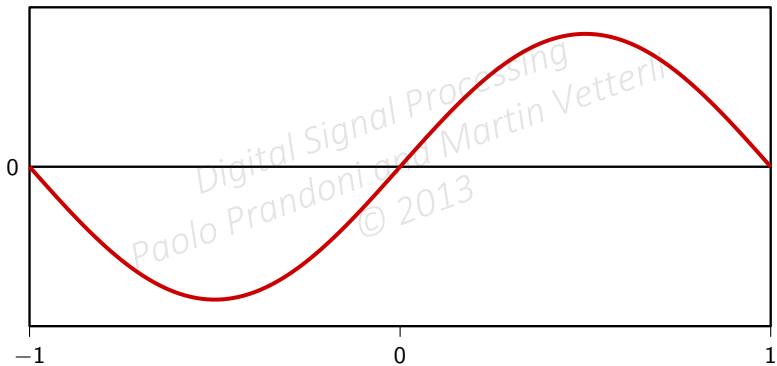


$$\langle \mathbf{x}, \mathbf{y} \rangle = \sqrt{(x_0^2 + x_1^2)(y_0^2 + y_1^2)} \cos \alpha$$

$$\langle \mathbf{x}, \mathbf{y} \rangle = x_0 y_0 + x_1 y_1$$

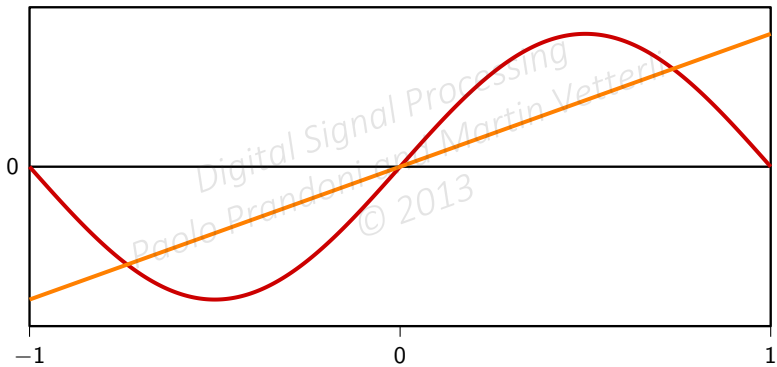


$$\langle \mathbf{x}, \mathbf{y} \rangle = \int_{-1}^1 x(t)y(t)dt$$



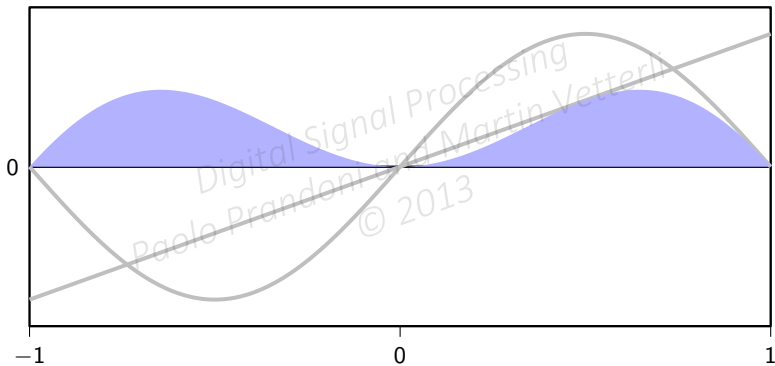
$$\mathbf{x} = \sin(\pi t)$$

$$\langle \mathbf{x}, \mathbf{y} \rangle = \int_{-1}^1 x(t)y(t)dt$$

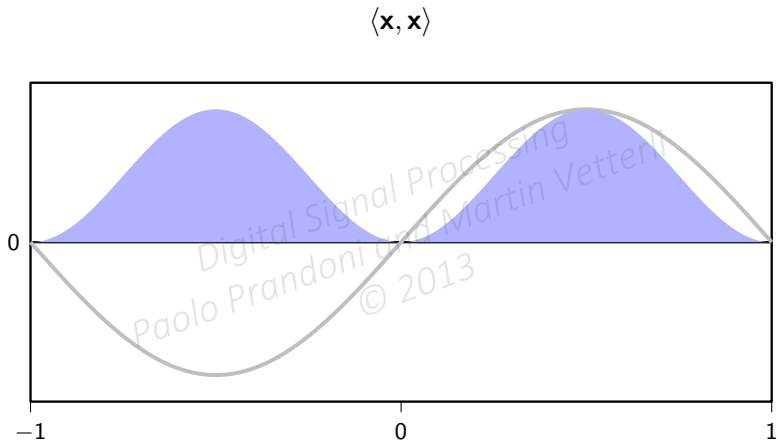


$$\mathbf{y} = t$$

$$\langle \mathbf{x}, \mathbf{y} \rangle = \int_{-1}^1 t \sin(\pi t) dt$$

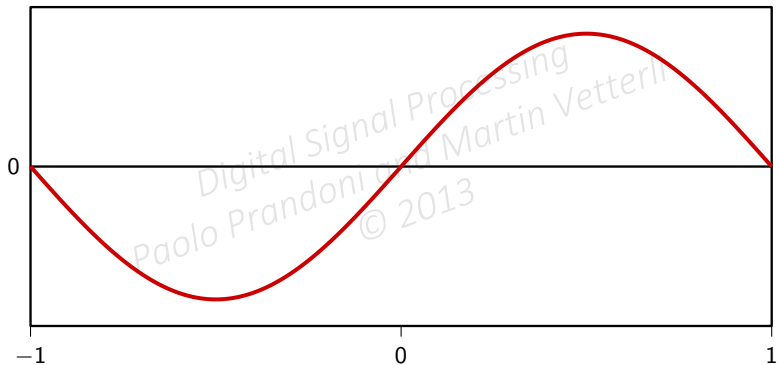


$$\langle \mathbf{x}, \mathbf{y} \rangle = 2/\pi \approx 0.6367$$



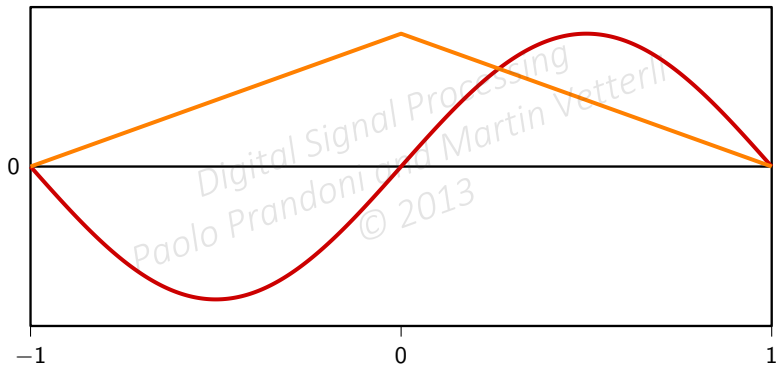
$$\mathbf{x} = \sin(\pi t), \langle \mathbf{x}, \mathbf{x} \rangle = 1$$

\mathbf{x}, \mathbf{y} from orthogonal subspaces



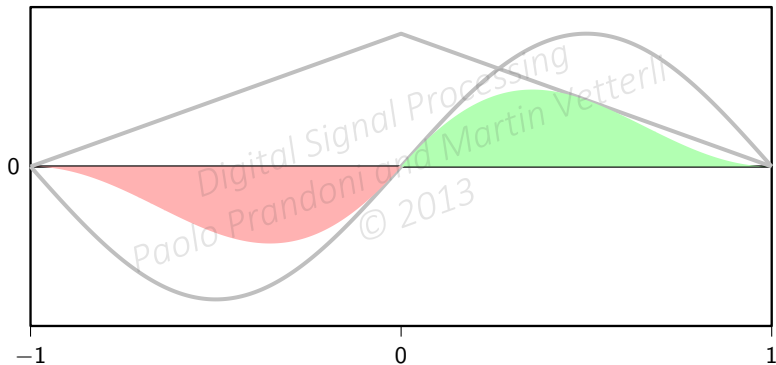
$\mathbf{x} = \sin(\pi t)$, antisymmetric

\mathbf{x}, \mathbf{y} from orthogonal subspaces



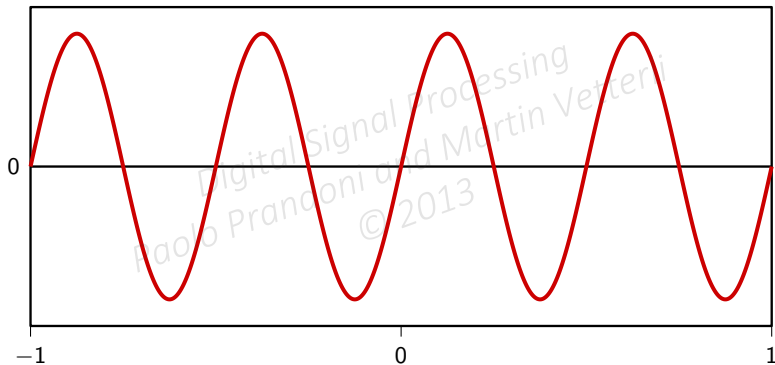
$\mathbf{y} = 1 - |t|$, symmetric

\mathbf{x}, \mathbf{y} from orthogonal subspaces



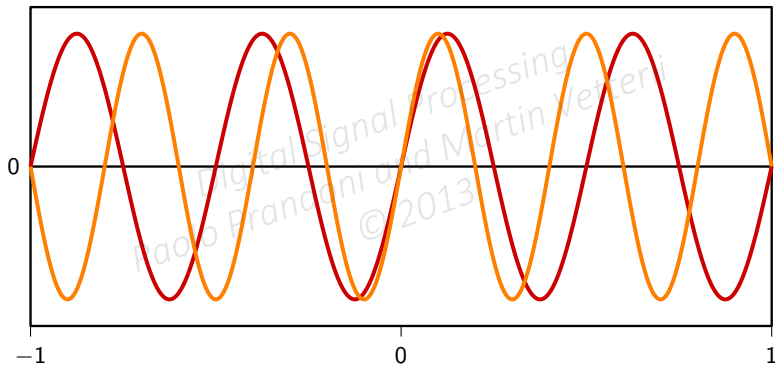
$$\langle \mathbf{x}, \mathbf{y} \rangle = 0$$

sinusoids with frequencies integer multiples of a fundamental



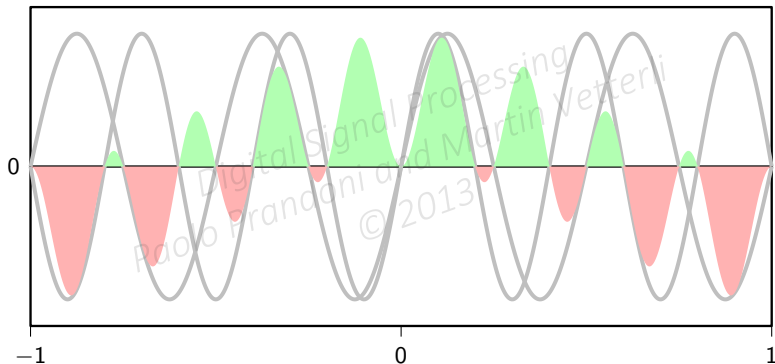
$$x = \sin(4\pi t)$$

sinusoids with frequencies integer multiples of a fundamental



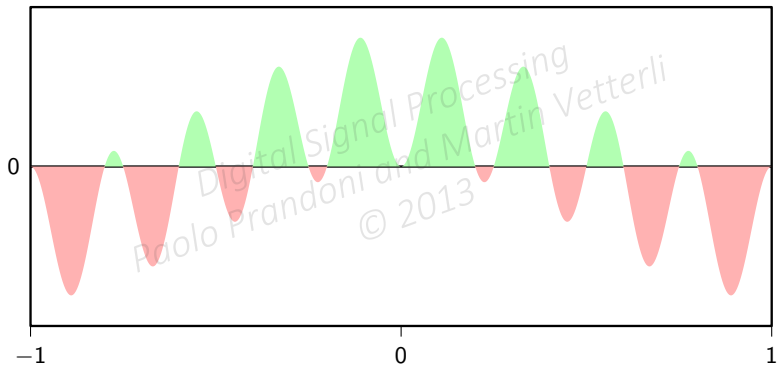
$$\mathbf{x} = \sin(4\pi t) , \quad \mathbf{y} = \sin(5\pi t)$$

sinusoids with frequencies integer multiples of a fundamental



$$\mathbf{x} = \sin(4\pi t) , \quad \mathbf{y} = \sin(5\pi t) , \quad \langle \mathbf{x}, \mathbf{y} \rangle = 0$$

sinusoids with frequencies integer multiples of a fundamental



$$\langle \mathbf{x}, \mathbf{y} \rangle = 0$$

For $\mathbf{x}, \mathbf{y}, \mathbf{z} \in V$ and $\alpha \in \mathbb{C}$:

- ▶ $\langle \mathbf{x} + \mathbf{y}, \mathbf{z} \rangle = \langle \mathbf{x}, \mathbf{z} \rangle + \langle \mathbf{y}, \mathbf{z} \rangle$
- ▶ $\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{y}, \mathbf{x} \rangle^*$
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 $\langle \mathbf{x}, \alpha \mathbf{y} \rangle = \alpha \langle \mathbf{x}, \mathbf{y} \rangle$
- ▶ $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$
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► $\langle \alpha \mathbf{x}, \mathbf{y} \rangle = \alpha^* \langle \mathbf{x}, \mathbf{y} \rangle$
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$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{n=0}^{N-1} x^*[n]y[n]$$

well defined for all finite-length vectors (i.e. vectors in \mathbb{C}^N)

$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{n=-\infty}^{\infty} x^*[n]y[n]$$

careful: sum may explode!

$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{n=-\infty}^{\infty} x^*[n]y[n]$$

We require sequences to be *square-summable*: $\sum |x[n]|^2 < \infty$

Space of square-summable sequences: $\ell_2(\mathbb{Z})$

► inner product defines a norm: $\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}$

► norm defines a distance: $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$

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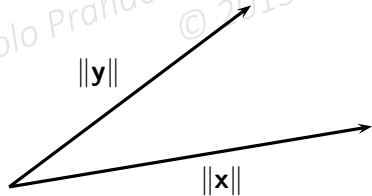
$$\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle} = \sqrt{x_0^2 + x_1^2}$$

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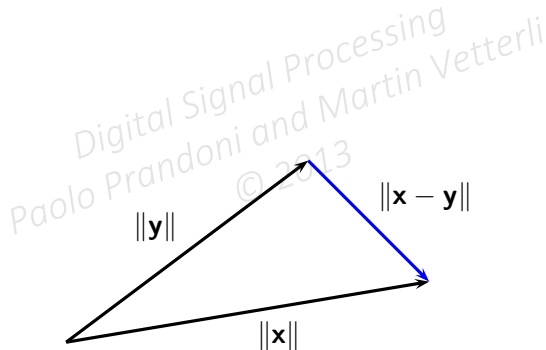


$$\|\mathbf{y}\| = \sqrt{\langle \mathbf{y}, \mathbf{y} \rangle} = \sqrt{y_0^2 + y_1^2}$$

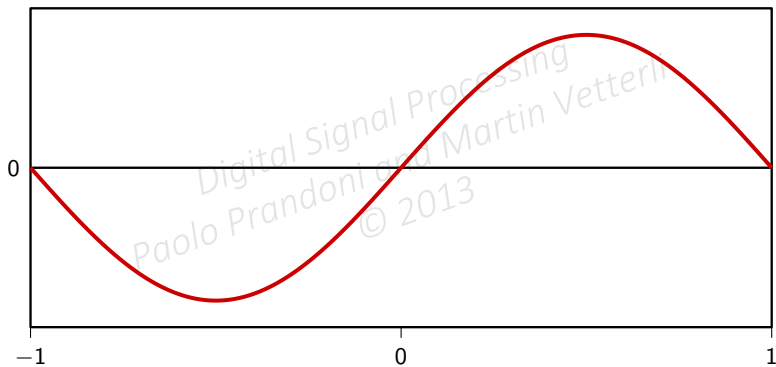
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$$\|\mathbf{x} - \mathbf{y}\| = \sqrt{(x_0 - y_0)^2 + (x_1 - y_1)^2}$$

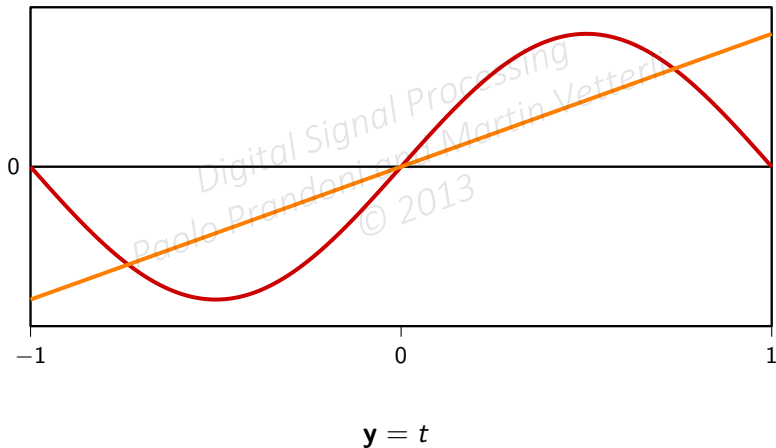


$$\|\mathbf{x} - \mathbf{y}\|^2 = \int_{-1}^1 |x(t) - y(t)|^2 dt \text{ (MSE)}$$

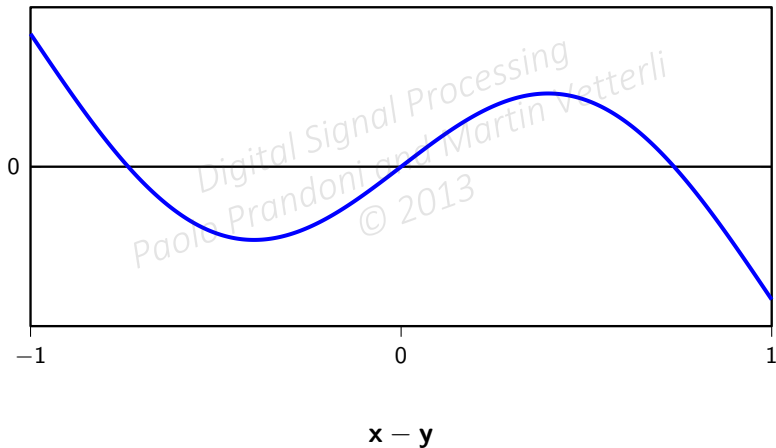


$$\mathbf{x} = \sin(\pi t)$$

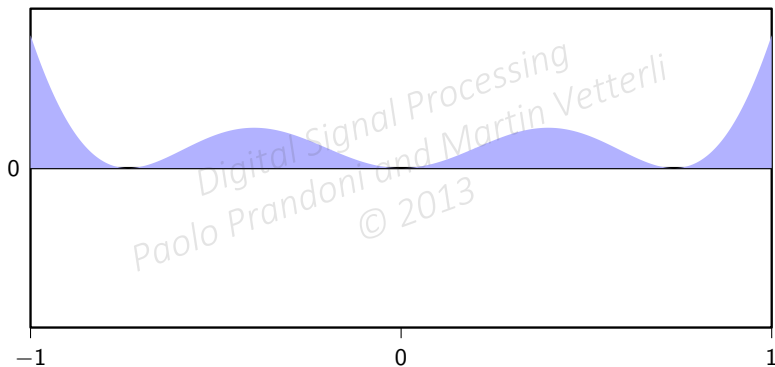
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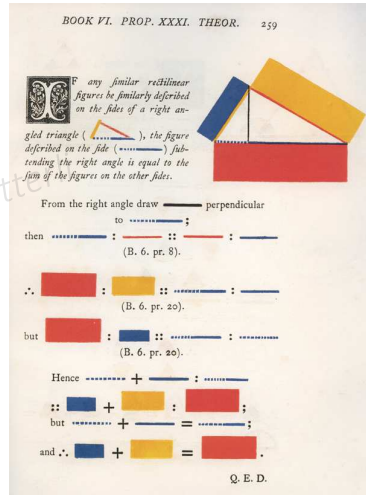
$$\|\mathbf{x} - \mathbf{y}\|^2 = \int_{-1}^1 |x(t) - y(t)|^2 dt \text{ (MSE)}$$



$$\|\mathbf{x} - \mathbf{y}\| = \sqrt{5/3 - 4/\pi} \approx 0.6272$$

Pythagorean theorem:

$$\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 \text{ for } \mathbf{x} \perp \mathbf{y}$$



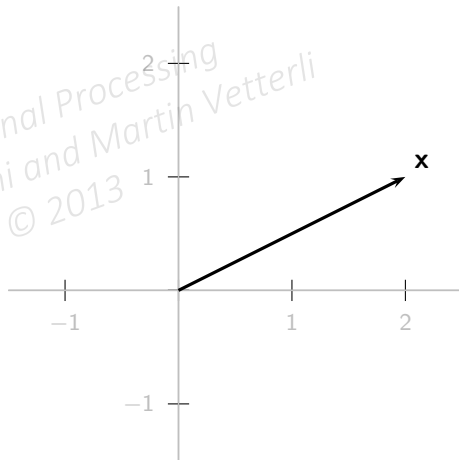
From Euclid's elements by Oliver Byrne (1810 - 1880)

$$\mathbf{x} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \in \mathbb{R}^2$$

$$\mathbf{x} = 2\mathbf{e}^{(0)} + \mathbf{e}^{(1)}$$

$$\mathbf{x} = \mathbf{v}^{(0)} + \mathbf{v}^{(1)}$$

$$\mathbf{x} \neq \alpha_0 \mathbf{g}^{(0)} + \alpha_1 \mathbf{g}^{(1)} \quad \text{for any } \alpha_0, \alpha_1$$

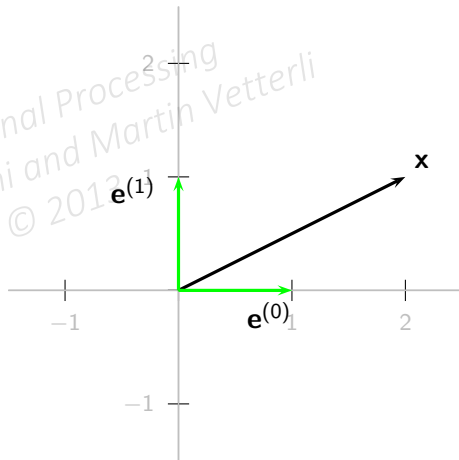


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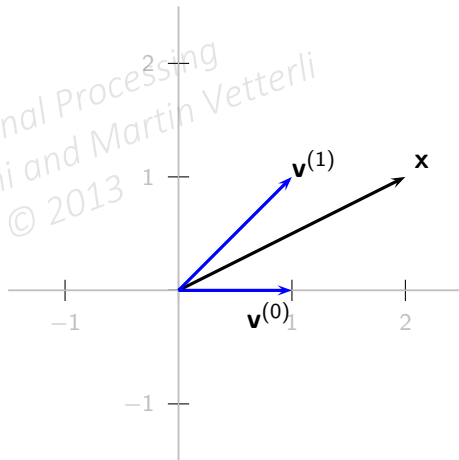


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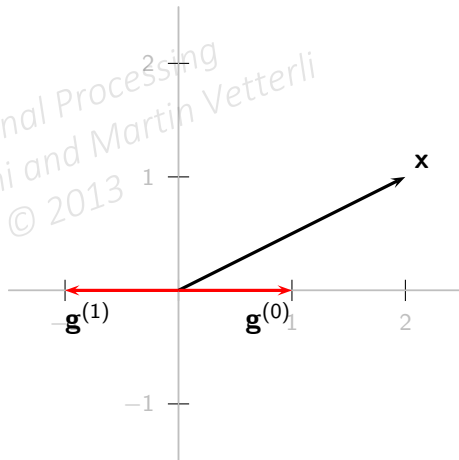


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- ▶ vector space H
- ▶ set of K vectors from H : $W = \{\mathbf{w}^{(k)}\}_{k=0,1,\dots,K-1}$

W is a basis for H if:

- ▶ we can write for *all* $\mathbf{x} \in H$:

$$\mathbf{x} = \sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)}, \quad \alpha_k \in \mathbb{C}$$

- ▶ the coefficients α_k are unique

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Unique representation implies linear independence:

$$\sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)} = \mathbf{0} \iff \alpha_k = 0, \quad k = 0, 1, \dots, K-1$$

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Orthogonal basis:

$$\langle \mathbf{w}^{(k)}, \mathbf{w}^{(n)} \rangle = 0 \text{ for } k \neq n$$

Orthonormal basis:

$$\langle \mathbf{w}^{(k)}, \mathbf{w}^{(n)} \rangle = \delta[n - k]$$

We can always orthonormalize a basis via the Gram-Schmidt algorithm.

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$$\mathbf{x} = \sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)}$$

How do we find the α 's ?

Orthonormal bases are the best:

$$\alpha_k = \langle \mathbf{w}^{(k)}, \mathbf{x} \rangle$$

$$\mathbf{x} = \sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)}$$

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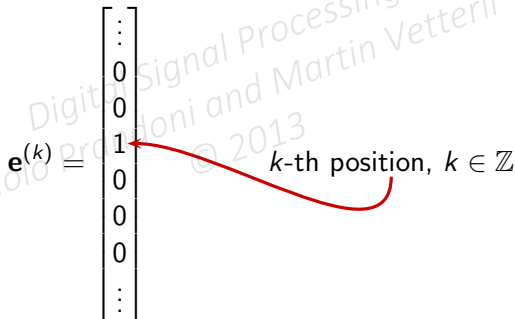
- ▶ a basis will contain N vectors
- ▶ canonical (orthonormal) basis:

$$\mathbf{e}^{(k)} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

k -th position, $0 \leq k < N$

Example: bases for sequences in $\ell_2(\mathbb{Z})$

- ▶ a basis will contain infinite vectors
- ▶ canonical (orthonormal) basis:


$$\mathbf{e}^{(k)} = \begin{bmatrix} \vdots \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ \vdots \end{bmatrix}$$

k -th position, $k \in \mathbb{Z}$

limiting operations must yield vector space elements

Example of an *incomplete* space: the set of rational numbers

$$x_n = \sum_{k=1}^n \frac{1}{k!} \in \mathbb{Q} \quad \text{but} \quad \lim_{n \rightarrow \infty} x_n = e \notin \mathbb{Q}$$

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limiting operations must yield vector space elements

Example of an *incomplete* space: the set of rational numbers

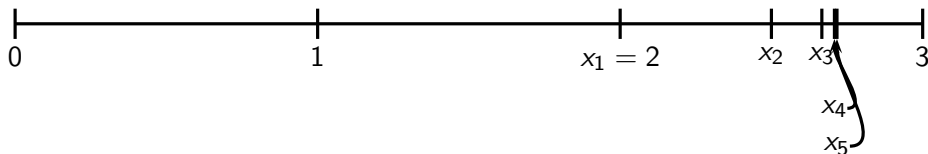
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END OF MODULE 3.2

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Module 3.3: Hilbert Space and approximation

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- ▶ Norm conservation, Parseval

- ▶ Approximation by projection

- ▶ Examples

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- ▶ Norm conservation, Parseval
- ▶ Approximation by projection
- ▶ Examples

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- ▶ Norm conservation, Parseval
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- ▶ Examples

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$$\mathbf{x} = \sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)}$$

For an orthonormal basis:

$$\|\mathbf{x}\|^2 = \sum_{k=0}^{K-1} |\alpha_k|^2$$

$$\mathbf{x} = \sum_{k=0}^{K-1} \alpha_k \mathbf{w}^{(k)}$$

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► canonical basis $E = \{\mathbf{e}^{(0)}, \mathbf{e}^{(1)}\}$

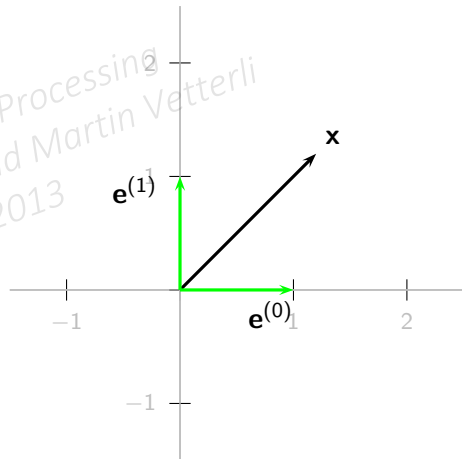
► $\mathbf{x} = \alpha_0 \mathbf{e}^{(0)} + \alpha_1 \mathbf{e}^{(1)}$

► new basis $V = \{\mathbf{v}^{(0)}, \mathbf{v}^{(1)}\}$ with

$$\mathbf{v}^{(0)} = [\cos \theta \ \sin \theta]^T$$

$$\mathbf{v}^{(1)} = [-\sin \theta \ \cos \theta]^T$$

► $\mathbf{x} = \beta_0 \mathbf{v}^{(0)} + \beta_1 \mathbf{v}^{(1)}$



► canonical basis $E = \{\mathbf{e}^{(0)}, \mathbf{e}^{(1)}\}$

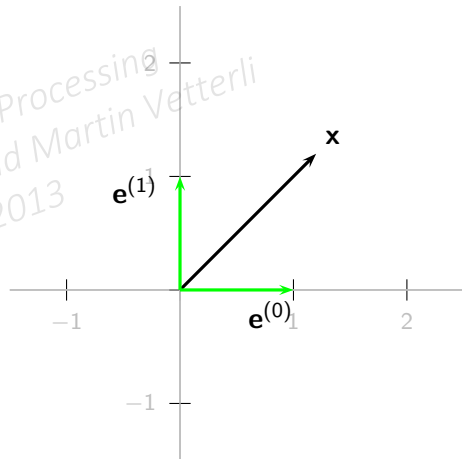
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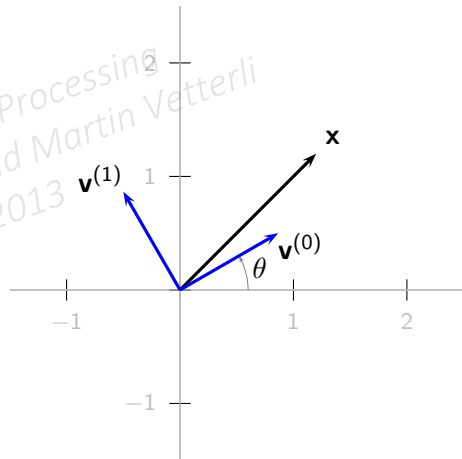
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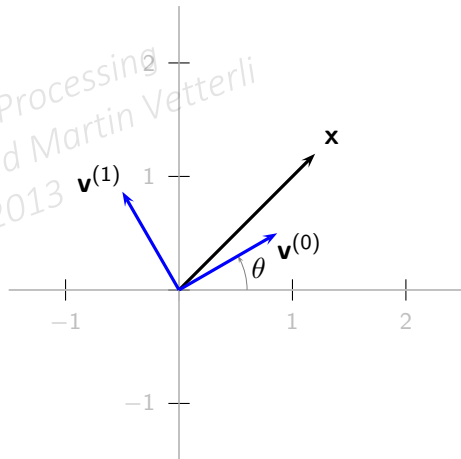
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► $\mathbf{x} = \beta_0 \mathbf{v}^{(0)} + \beta_1 \mathbf{v}^{(1)}$



- ▶ new basis is orthonormal:

$$\beta_0 = \langle \mathbf{v}^{(0)}, \mathbf{x} \rangle$$

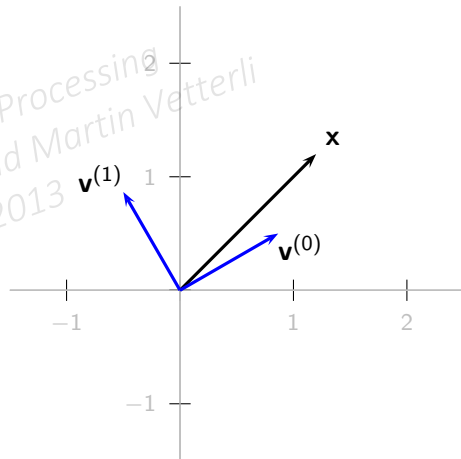
$$\beta_1 = \langle \mathbf{v}^{(1)}, \mathbf{x} \rangle$$

- ▶ in compact form:

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \mathbf{R} \boldsymbol{\alpha}$$

- ▶ \mathbf{R} : rotation matrix

- ▶ key fact: $\mathbf{R}^T \mathbf{R} = \mathbf{I}$



- ▶ new basis is orthonormal:

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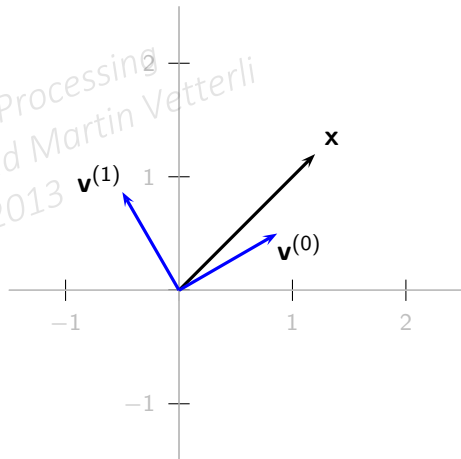
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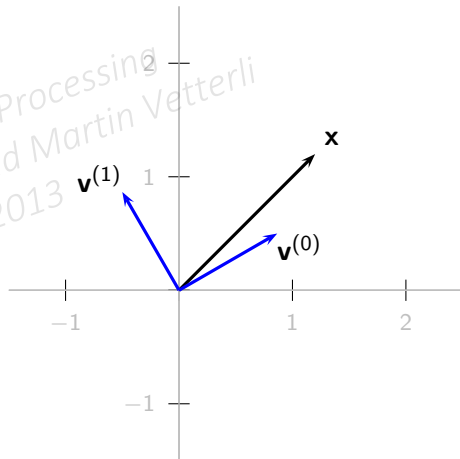
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- ▶ **R**: rotation matrix

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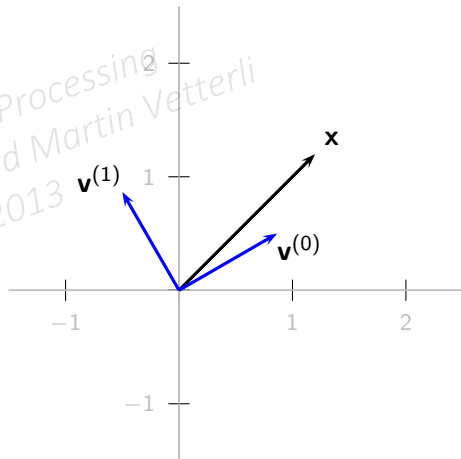
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$$\beta_1 = \langle \mathbf{v}^{(1)}, \mathbf{x} \rangle$$

- ▶ in compact form:

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \mathbf{R} \boldsymbol{\alpha}$$

- ▶ \mathbf{R} : rotation matrix
- ▶ key fact: $\mathbf{R}^T \mathbf{R} = \mathbf{I}$



- ▶ square norm in canonical basis: $\|\mathbf{x}\|^2 = \alpha_0^2 + \alpha_1^2$
- ▶ square norm in rotated basis: $\|\mathbf{x}\|^2 = \beta_0^2 + \beta_1^2$
- ▶ let's verify Parseval:

$$\begin{aligned}\beta_0^2 + \beta_1^2 &= \beta^T \beta \\ &= (\mathbf{R}\alpha)^T (\mathbf{R}\alpha) \\ &= \alpha^T (\mathbf{R}^T \mathbf{R}) \alpha \\ &= \alpha^T \alpha \\ &= \alpha_0^2 + \alpha_1^2\end{aligned}$$

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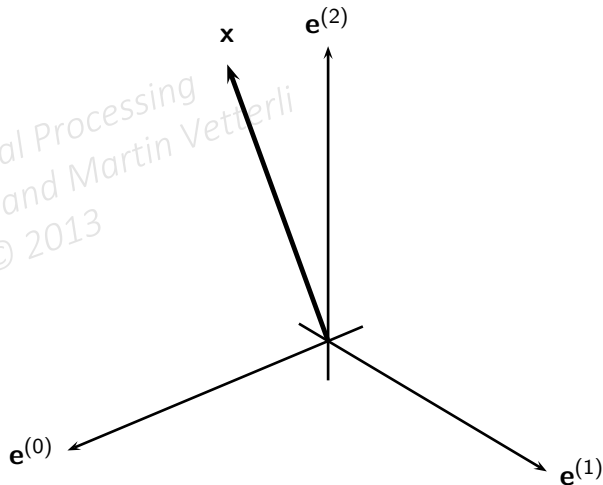
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Problem:

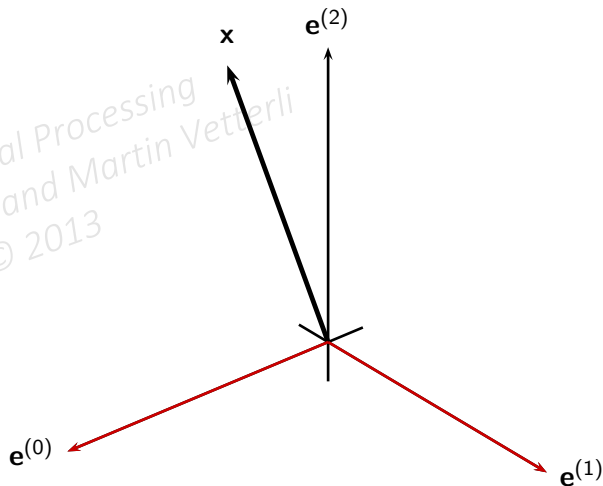
- ▶ vector $\mathbf{x} \in V$
- ▶ subspace $S \subseteq V$
- ▶ approximate \mathbf{x} with $\hat{\mathbf{x}} \in S$



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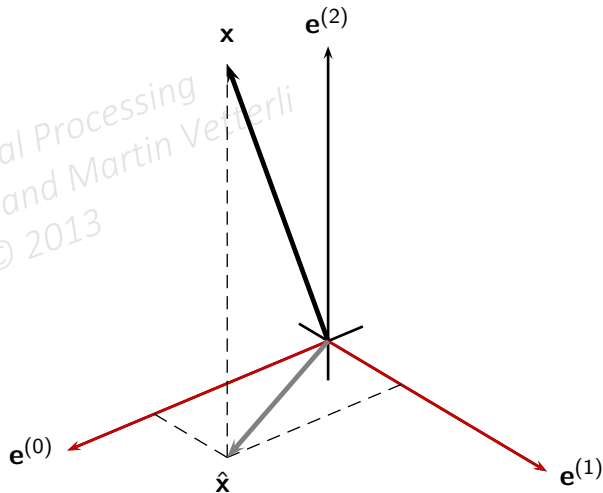
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- ▶ $\{\mathbf{s}^{(k)}\}_{k=0,1,\dots,K-1}$ orthonormal basis for S

- ▶ orthogonal projection:

$$\hat{\mathbf{x}} = \sum_{k=0}^{K-1} \langle \mathbf{s}^{(k)}, \mathbf{x} \rangle \mathbf{s}^{(k)}$$

orthogonal projection is the “best” approximation over S

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- ▶ orthogonal projection has minimum-norm error:

$$\arg \min_{\mathbf{y} \in S} \|\mathbf{x} - \mathbf{y}\| = \hat{\mathbf{x}}$$

- ▶ error is orthogonal to approximation:

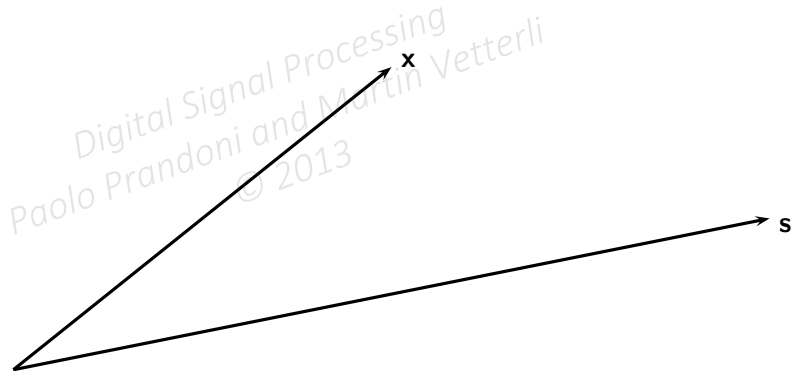
$$\langle \mathbf{x} - \hat{\mathbf{x}}, \hat{\mathbf{x}} \rangle = 0$$

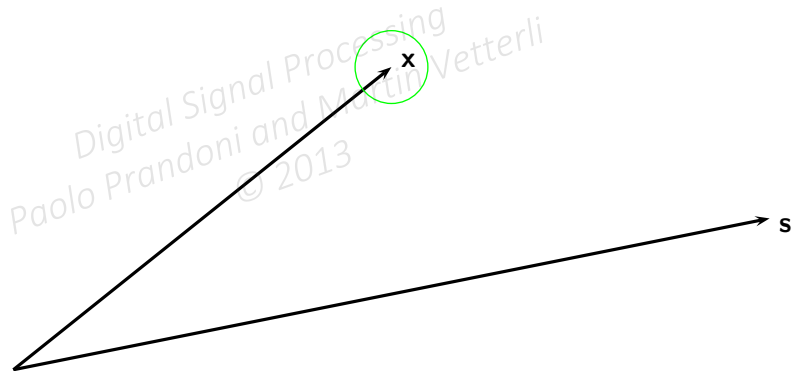
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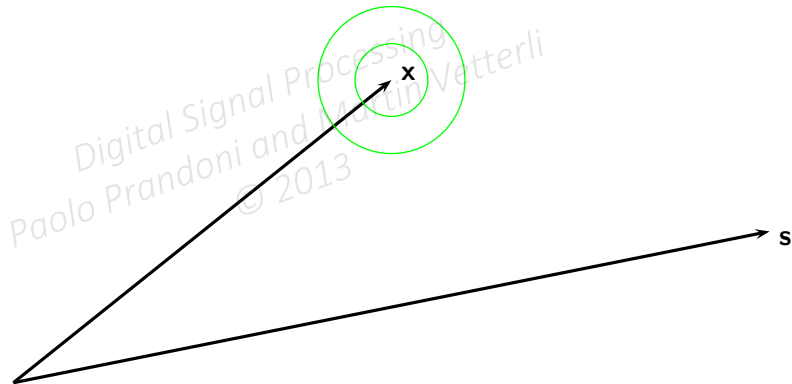
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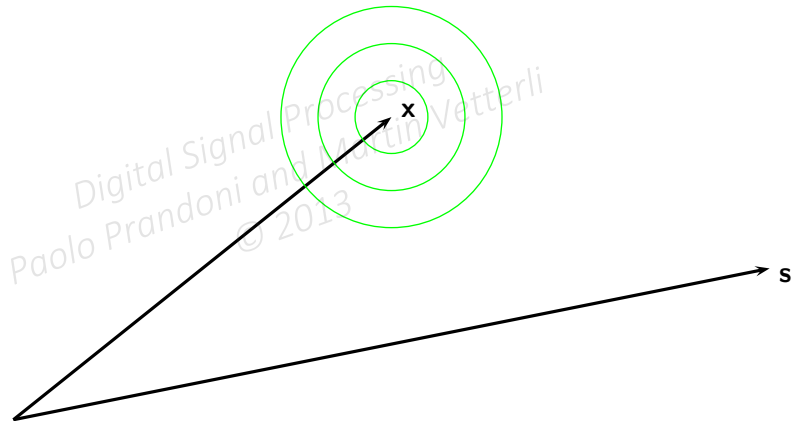
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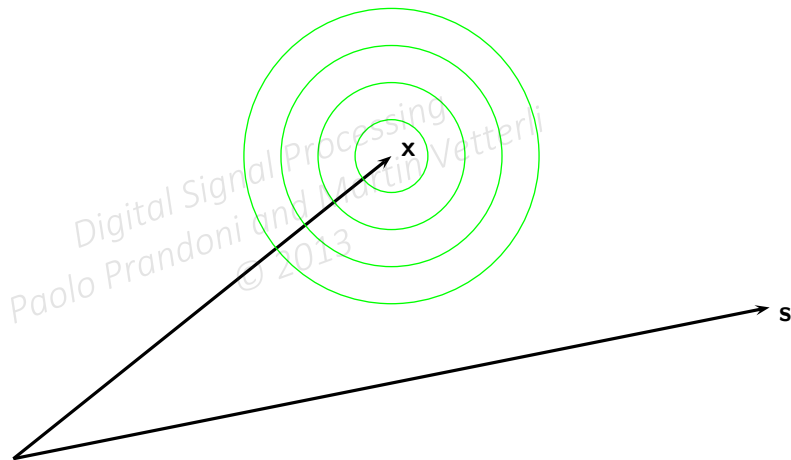
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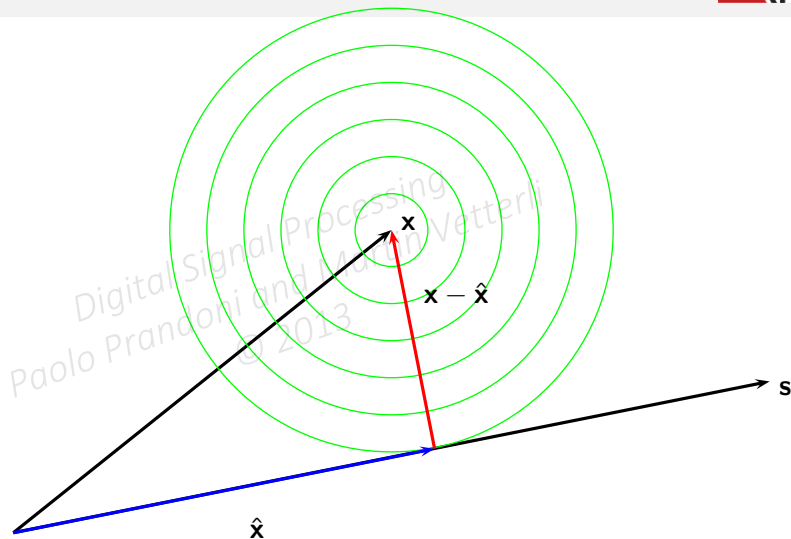












- ▶ Hilbert space $P_N[-1, 1] \subset L_2[-1, 1]$
- ▶ a self-evident, naive basis: $s^{(k)}(t) = t^k, k = 0, 1, \dots, N - 1$
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goal: approximate $\mathbf{x} = \sin t$ over $P_3[-1, 1]$

- ▶ build orthonormal basis from naive basis
- ▶ project \mathbf{x} over the orthonormal basis
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- ▶ compare error to Taylor approximation (well known but not optimal over the interval)

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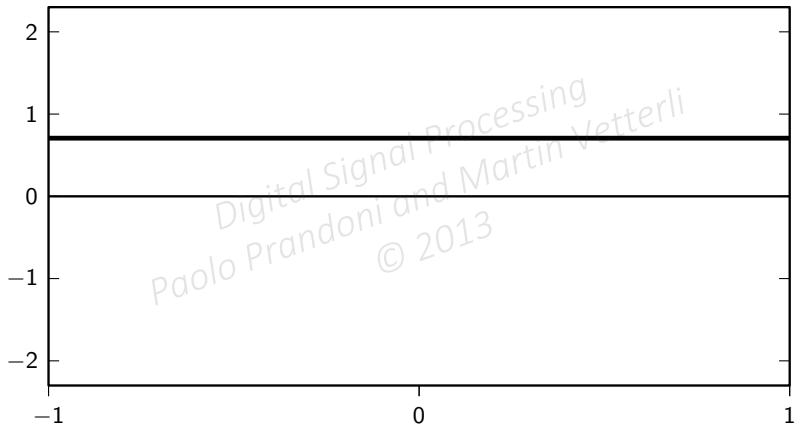
The Gram-Schmidt algorithm leads to an orthonormal basis for $P_N([-1, 1])$
(see appendix if interested in details)

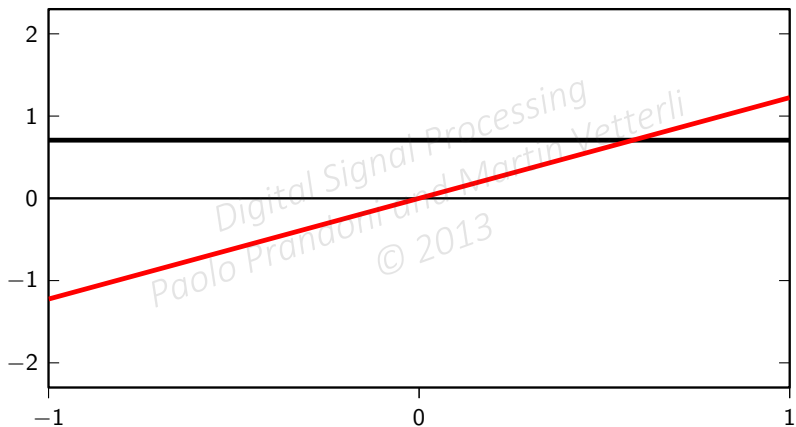
$$\mathbf{u}^{(0)} = \sqrt{1/2}$$

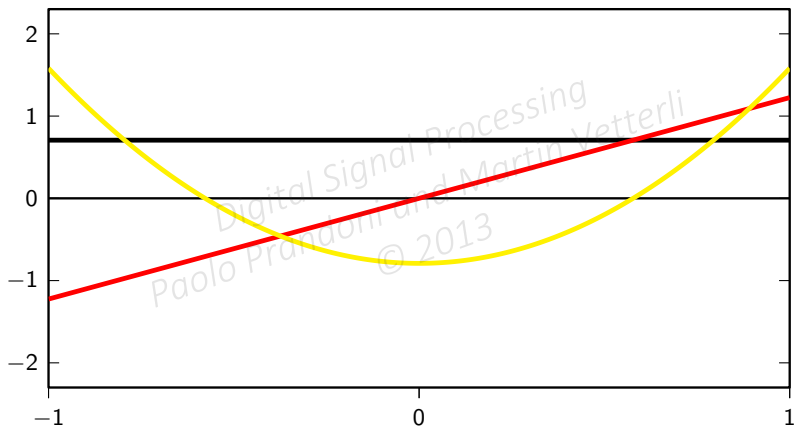
$$\mathbf{u}^{(1)} = \sqrt{3/2} t$$

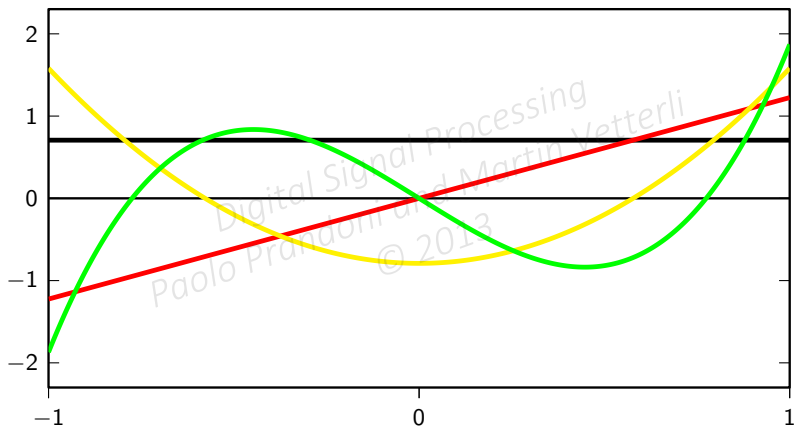
$$\mathbf{u}^{(2)} = \sqrt{5/8}(3t^2 - 1)$$

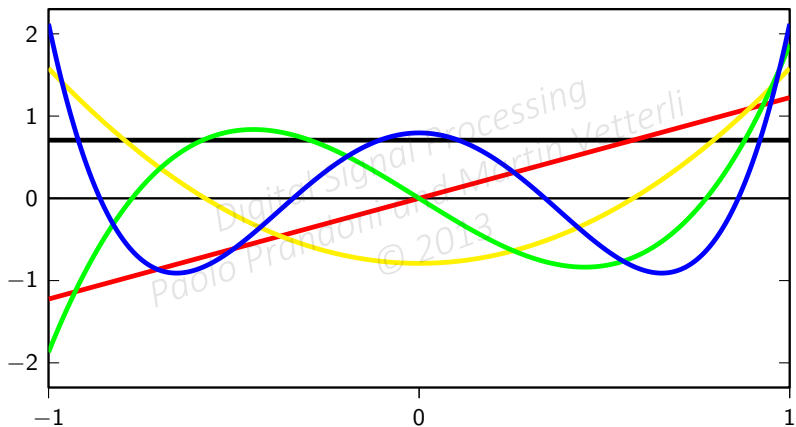
$$\mathbf{u}^{(3)} = \dots$$

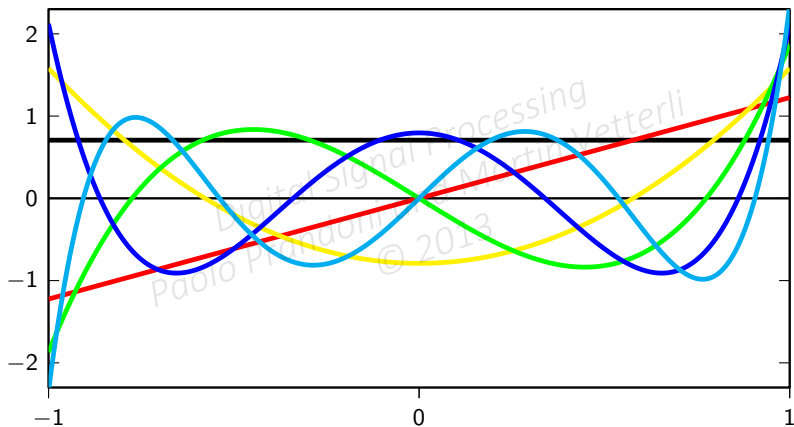












$$\alpha_k = \langle \mathbf{u}^{(k)}, \mathbf{x} \rangle = \int_{-1}^1 u_k(t) \sin t \, dt$$

► $\alpha_0 = \langle \sqrt{1/2}, \sin t \rangle = 0$

► $\alpha_1 = \langle \sqrt{3/2} t, \sin t \rangle \approx 0.7377$

► $\alpha_2 = \langle \sqrt{5/8}(3t^2 - 1), \sin t \rangle = 0$

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Using the orthogonal projection over $P_3[-1, 1]$:

$$\sin t \rightarrow \alpha_1 \mathbf{u}^{(1)} \approx 0.9035 t$$

Using Taylor's series:

$$\sin t \approx t$$

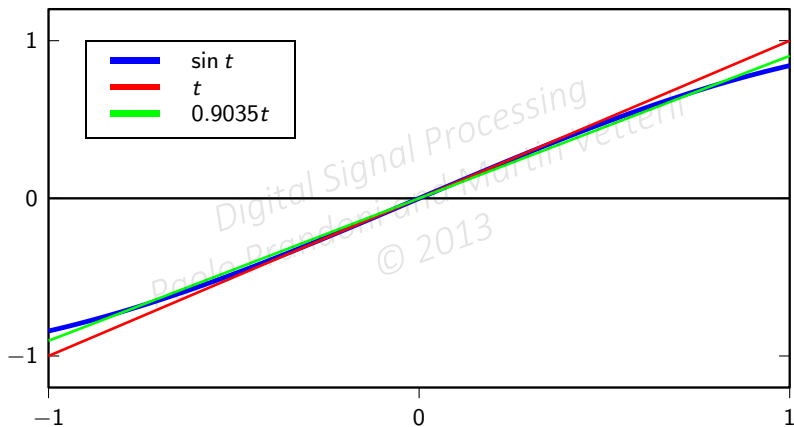
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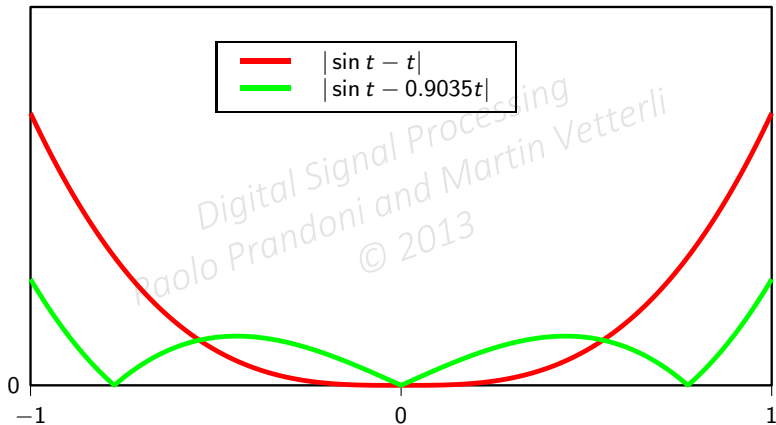
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Orthogonal projection over $P_3[-1, 1]$:

$$\|\sin t - \alpha_1 \mathbf{u}^{(1)}\| \approx 0.0337$$

Taylor series:

$$\|\sin t - t\| \approx 0.0857$$

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Why do we do all this?

- ▶ finite-length and periodic signals live in \mathbb{C}^N
- ▶ infinite-length signals live in $\ell_2(\mathbb{Z})$
- ▶ different bases are different observation tools for signals
- ▶ subspace projections are useful in filtering and compression

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END OF MODULE 3.3

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Appendix: orthonormalization of the naive polynomial basis

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Gram-Schmidt orthonormalization procedure:

$$\{\mathbf{s}^{(k)}\} \longrightarrow \{\mathbf{u}^{(k)}\}$$

original set orthonormal set

Algorithmic procedure: at each step k

1. $\mathbf{p}^{(k)} = \mathbf{s}^{(k)} - \sum_{n=0}^{k-1} \langle \mathbf{u}^{(n)}, \mathbf{s}^{(k)} \rangle \mathbf{u}^{(n)}$

2. $\mathbf{u}^{(k)} = \mathbf{p}^{(k)} / \|\mathbf{p}^{(k)}\|$

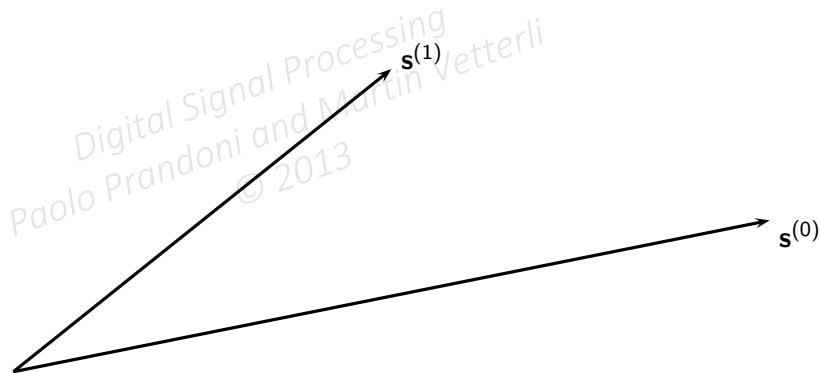
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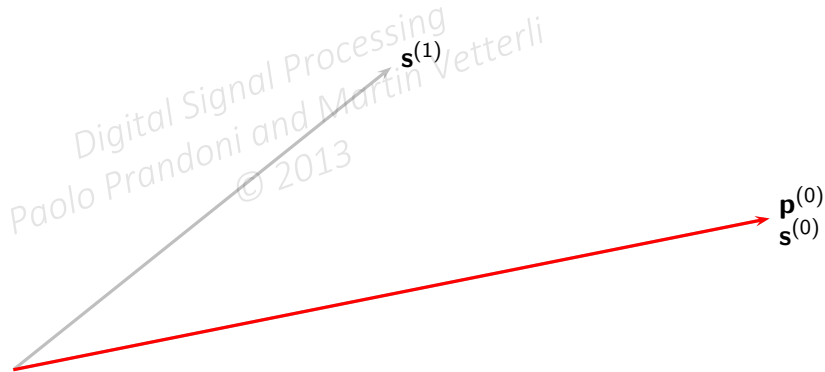
$$\begin{array}{ccc} \{\mathbf{s}^{(k)}\} & \longrightarrow & \{\mathbf{u}^{(k)}\} \\ \text{original set} & & \text{orthonormal set} \end{array}$$

Algorithmic procedure: at each step k

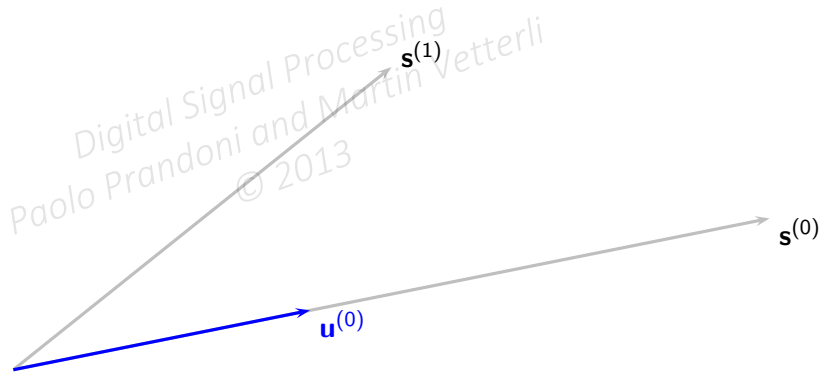
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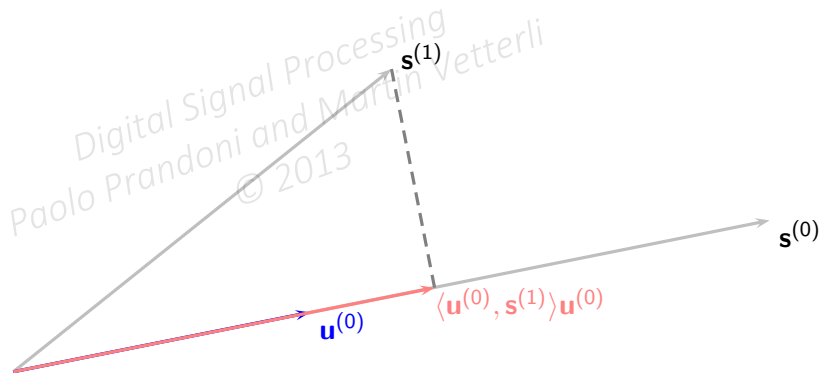
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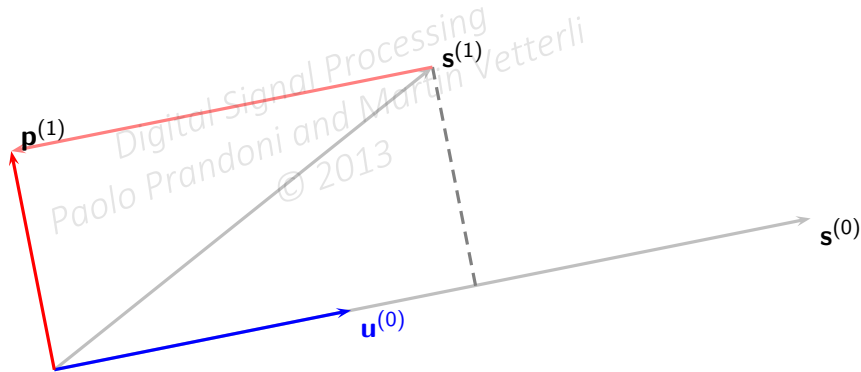


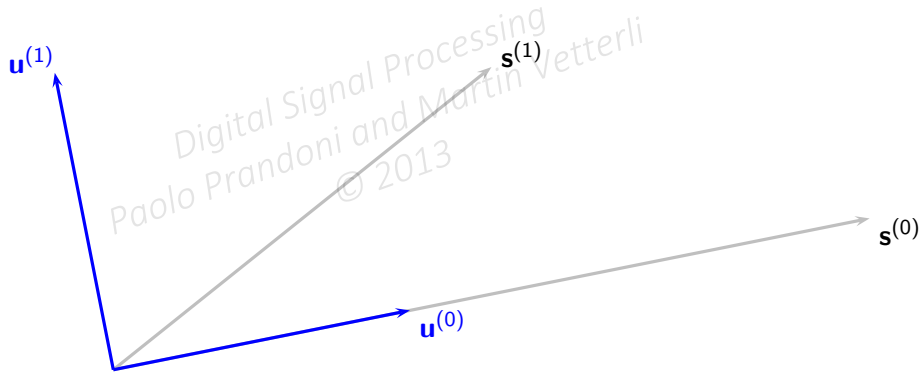


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Gram-Schmidt orthonormalization of the naive basis: $\{\mathbf{s}^{(k)}\} \rightarrow \{\mathbf{u}^{(k)}\}$

► $\mathbf{s}^{(0)} = 1$

- $\mathbf{p}^{(0)} = \mathbf{s}^{(0)} = 1$

- $\|\mathbf{p}^{(0)}\|^2 = 2$

- $\mathbf{u}^{(0)} = \mathbf{p}^{(0)} / \|\mathbf{p}^{(0)}\| = 1/\sqrt{2}$

► $\mathbf{s}^{(1)} = t$

- $\langle \mathbf{u}^{(0)}, \mathbf{s}^{(1)} \rangle = \int_{-1}^1 t / \sqrt{2} = 0$

- $\mathbf{p}^{(1)} = \mathbf{s}^{(1)} = t$

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► $\mathbf{s}^{(2)} = t^2$

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- $\langle \mathbf{u}^{(0)}, \mathbf{s}^{(1)} \rangle = \int_{-1}^1 t / \sqrt{2} = 0$

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- $\mathbf{p}^{(2)} = \mathbf{s}^{(2)} - (2/3\sqrt{2})\mathbf{u}^{(0)} = t^2 - 1/3$

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$$\mathbf{u}^{(0)} = \sqrt{1/2}$$

$$\mathbf{u}^{(1)} = \sqrt{3/2} t$$

$$\mathbf{u}^{(2)} = \sqrt{5/8} (3t^2 - 1)$$

$$\mathbf{u}^{(3)} = \dots$$

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END OF MODULE 3

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