



# Fundamentals of Signal Decompositions

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# 1. Vector spaces and Inner Products

## Linear Algebra:

- ✍ Vectors over  $R$  or  $C$  that are of a finite dimension  $n$ :  $R^n$  or  $C^n$
- ✍ Given  $\{v_k\}$  a set of vectors in these spaces:
  - ☯ Does the set span the spaces, i.e. can every vector be represented as a linear combination of vectors from  $\{v_k\}$ ?
  - ☯ Are the vectors linearly independent?
  - ☯ How can we find bases for the spaces to be spanned?
  - ☯ Given a subspace in  $R^n$  or  $C^n$  and a general vector  $x$ , can we find an approximation of  $x$  in the least-square sense that lies in the subspace?

# 1. Vector spaces and Inner Products

- A *vector space* over  $R$  or  $C$  is a set of vectors  $V$ , together with *addition* and scalar *multiplication*.
- Properties:
  - ✍ Commutativity:  $x + y = y + x$
  - ✍ Associativity:  $(x + y) + z = x + (y + z)$
  - ✍ Distributivity:  $\alpha(x + y) = \alpha x + \alpha y$
  - ✍ Additive Identity: there exists  $0$  in  $V$ , such that:  $x + 0 = x, \forall x \in V$
  - ✍ Multiplicative Identity:  $1 \cdot x = x, \forall x \in V$
  - ✍ Additive inverse: for all  $x$  in  $V$ , there exists a  $(-x)$  in  $V$ , such that:  $x + (-x) = 0$
- A subset  $M$  of  $V$  is a *subspace* of  $V$  if:
  - ✍ For all  $x$  and  $y$  in  $M$ ,  $x+y$  is in  $M$
  - ✍ For all  $x$  in  $M$ , and  $\alpha$  in  $R$  or  $C$ ,  $\alpha x$  is in  $M$ .
- Given  $S \subset V$ , the *span* of  $S$  is the subspace of  $V$  consisting of all linear combinations of vectors in  $S$ .
  - ✍ Example:  $span(S) = \left\{ \sum_{i=1}^n \alpha_i x_i \mid \forall \alpha_i \in C, \forall x_i \in S \right\}$

# 1. Vector spaces and Inner Products

- The vectors  $\{x_1, x_2, \dots, x_n\}$  are *linearly independent* if  $\sum_i \alpha_i x_i = 0 \Rightarrow \alpha_i = 0, \forall i$
- A *basis* in  $V$  is a subset of linearly independent vectors  $\{x_1, x_2, \dots, x_n\}$  for which:  
 $E = \text{span}(x_1 \dots x_n)$
- $V$  is *infinite dimensional* if it contains an infinite linearly independent set of vectors;
  - ✍ eg.: the space of infinite sequences is spanned by the infinite set  $\{\delta(n - k)\}_{k \in \mathbb{Z}}$
- The *inner product* on  $V$  over  $\mathbb{C}$  is a function defined on  $V \times V$  with the properties:
  - ✍  $\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$
  - ✍  $\langle x, \alpha y \rangle = \alpha \langle x, y \rangle$
  - ✍  $\langle x, y \rangle^* = \langle y, x \rangle$
  - ✍  $\langle x, x \rangle \geq 0$  and  $\langle x, x \rangle = 0$  if and only if  $x \equiv 0$
- Examples:
  - ✍ The inner product for complex-valued functions over  $\mathbb{R}$ :  $\langle f, g \rangle = \int_{-\infty}^{\infty} f(t) g^*(t) dt$
  - ✍ The inner product for complex-valued sequences over  $\mathbb{Z}$ :  $\langle x, y \rangle = \sum_{n=-\infty}^{\infty} x[n] y^*[n]$
- A vector space equipped with an inner product is called an *inner product space*

# 1. Vector spaces and Inner Products

- The *norm* of a vector is defined as:  $\|x\| = \sqrt{\langle x, x \rangle}$
- Examples of *inner-product spaces*:
  - ✍ The real-numbers  $\mathbb{R}$ :  $\langle x, y \rangle = xy$
  - ✍ The Euclidian space  $\mathbb{R}^n$  for which the inner product is the *dot product* between two vectors:  $\langle (x_1, x_2, \dots, x_n), (y_1, y_2, \dots, y_n) \rangle = \sum_{i=1}^n x_i y_i$
- One can introduce the notion of angle between two vectors:  $\langle x, y \rangle = \|x\| \cdot \|y\| \cdot \cos(\widehat{xy})$   
 $\Rightarrow$  Cauchy-Buniakowski-Schwartz inequality:
$$\langle x, y \rangle \leq \|x\| \cdot \|y\| \Leftrightarrow \left( \sum_{i=1}^n x_i y_i \right)^2 \leq \left( \sum_{i=1}^n x_i^2 \right) \left( \sum_{i=1}^n y_i^2 \right)$$
- Triangle inequality:  $\|x + y\| \leq \|x\| + \|y\|$
- Parallelogram law:  $\|x + y\|^2 + \|x - y\|^2 = 2\|x\|^2 + 2\|y\|^2$
- Pythagorean theorem: If  $\langle x, y \rangle = 0$  then:  $\|x + y\|^2 = \|x\|^2 + \|y\|^2$

# 1. Vector spaces and Inner Products

- A vector  $x$  is said to be *orthogonal* to a set of vectors  $S = \{y_i\}$ , if  $\langle x, y_i \rangle = 0, \forall i$   
✍ Notation:  $x \perp S$
- Two spaces  $S_1$  and  $S_2$  are called to be *orthogonal* if for  $\forall x_i \in S_1, x_i \perp S_2$   
✍ Notation:  $S_1 \perp S_2$
- A set of vectors  $\{x_1, x_2, \dots\}$  is called *orthogonal* if  $\forall i, j, i \neq j, x_i \perp x_j$
- A *orthonormal* set of vectors is an orthogonal set with unit norm:  $\langle x_i, x_j \rangle = \delta[i - j]$
- A sequence of vectors  $\{x_n\}$  in  $V$  is said to converge to a vector  $x$  in  $V$  if:  
$$\|x_n - x\| \rightarrow 0 \big|_{n \rightarrow \infty}$$
- A sequence of vectors  $\{x_n\}$  is called a *Cauchy* sequence if:  
$$\|x_n - x_m\| \rightarrow 0, \text{ as } n, m \rightarrow \infty$$
- If *every*(!) Cauchy sequence in  $V$  converges to a vector in  $V$ , then the space is  $V$  is called *complete*
- Note: Not all Cauchy sequences necessarily need to converge to a vector in  $V$ , i.e. not all vector spaces are necessarily complete

# 1. Vector spaces and Inner Products

- *A complete normed vector space is called a Banach space.*
- *Banach spaces: Every Cauchy sequence (with respect to the metric  $d(x, y) = \|x - y\|$ ) in  $V$  has a limit in  $V$*
- *Example: the space  $C[a, b]$  of all continuous real-valued or complex functions on the interval  $[a, b]$ , with the norm defined as:  $\|f\| = \sup\{|f(x)| : x \in [a, b]\}$* 
  - ✍ *Continuous functions on an interval are bounded, hence, the space is complete under this norm*
- *Another example: define the  $l^p$  norm:*
$$\|x\|_p = \left(|x_1|^p + |x_2|^p + \dots\right)^{1/p}$$
- *$l^p$  is the Banach space of all infinite sequences  $(x_1, x_2, \dots)$  of real or complex-valued elements, for which  $\|x\|_p$  is finite.*
  - ✍ *E.g.  $\left(1, \frac{1}{2}, \frac{1}{3}, \dots, \frac{1}{n}, \dots\right)$  is not in  $l^1$  but it is in  $l^p$*

# 1. Vector spaces and Inner Products

- *An inner-product space of which the norm is complete is called a Hilbert space.*
- Every inner-product gives rise to a norm, via the association:  $\langle x, x \rangle = \|x\|^2$
- If the norm is complete, then the space is called a Hilbert space
- Thus every Hilbert space is a Banach space by definition
- A necessary and sufficient condition for a Banach space  $V$  to be a Hilbert space is if the parallelogram rule is satisfied for all vectors  $x, y$  in  $V$

$$\|x + y\|^2 + \|x - y\|^2 = 2\|x\|^2 + 2\|y\|^2$$

- Example:  $\mathbb{R}^n$  is a Banach space for *any norm* defined on it, and it is a Hilbert space only with respect to the Euclidean norm
- Another example: define the  $L^p$  norm:  $\|f\|_p := \left( \int_a^b |f(x)|^p dx \right)^{1/p}$
- $L^p([a, b])$  is the Banach space of all real or complex-valued functions on  $[a, b]$ , for which  $L^p$  is finite  $L^p < \infty$
- This Banach space is a Hilbert space only for  $p = 2$



# 1.1. Vector spaces and Inner Products

- Examples of Hilbert spaces

- ✍ *Space of square-summable sequences -  $l^2(Z)$*

- ☯ inner product:  $\langle x, y \rangle = \sum_{n=-\infty}^{\infty} x[n] y^*[n]$

- ☯ norm:  $\|x\| = \sqrt{\langle x, x \rangle} = \sqrt{\sum_{n \in Z} |x[n]|^2} < \infty$

- ✍ *Space of square-integrable functions -  $L^2(R)$*

- ☯ inner product:  $\langle f, g \rangle = \int_{t \in R} f(t) g^*(t) dt$

- ☯ norm:  $\|f\| = \sqrt{\langle f, f \rangle} = \sqrt{\int_{t \in R} |f(t)|^2 dt}$

- Given a Hilbert space  $V$  and a subspace  $S$ , the *orthogonal complement* of  $S$  in  $V$ , denoted by  $S^\perp$  is the set  $\{x \in V, x \perp S\}$

- Given a vector  $x$  in  $V$ , there exists a unique  $y$  in  $S$  and a unique  $z$  in  $S^\perp$  such that  $x = y + z$ .

- ✍ Result:  $V = S \oplus S^\perp$

# 1. Vector spaces and Inner Products

## Orthonormal Bases in Hilbert spaces

- $S = \{x_i\}$  form an orthonormal basis in  $V$  if  $\langle x_i, x_j \rangle = \delta[i - j]$  and  $\forall y \in V, \exists \alpha_k,$

$$y = \sum_k \alpha_k x_k$$

- $\alpha_k = \langle x_k, y \rangle$

## Orthogonal Projection and Least-square Approximation

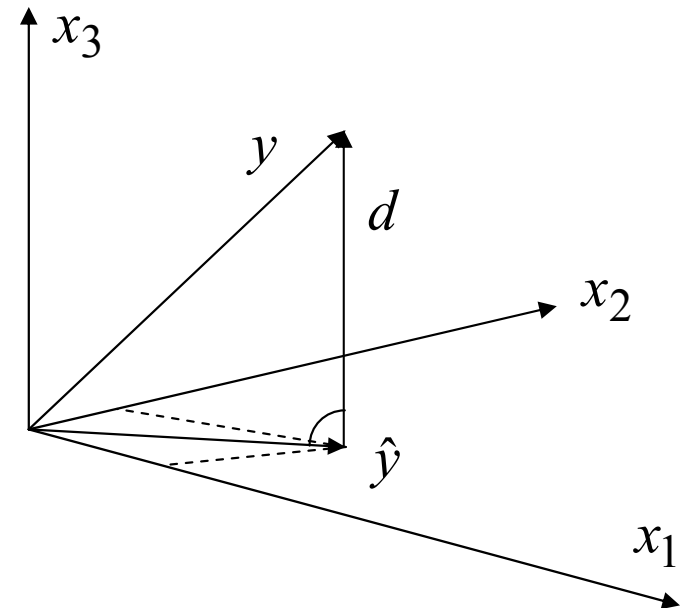
- Given  $V$  a Hilbert space,  $S$  a subspace of  $V$ ,  $\{x_1, x_2, \dots\}$  an orthonormal basis in  $S$ , and a vector  $y \in V$ , find the best approximation  $\hat{y}$  of  $y$  in  $S$ .

✎  $d = y - \hat{y}$

✎  $\|d\| = \|y - \hat{y}\|$  is minimal for  $\hat{y} = \sum_i \langle x_i, y \rangle x_i$

✎ Note that:  $d \perp S$ .

✎ Note that:  $\|y\|^2 = \|\hat{y}\|^2 + \|d\|^2$



# 1. Vector spaces and Inner Products

## Biorthogonal Bases

A system  $\{x_k, \tilde{x}_k\}$  constitutes *biorthogonal base* in a Hilbert space  $V$  if and only if:

- For all  $i, j$  in  $\mathbb{Z}$ :  $\langle x_i, \tilde{x}_j \rangle = \delta[i - j]$
- The sets  $\{x_k\}$  and  $\{\tilde{x}_k\}$  constitute each a *frame* in  $V$ , that is, for all  $y$  in  $V$ , there exist strictly positive constants  $A, B, \tilde{A}, \tilde{B}$  (called *frame bounds*) such that:

$$A\|y\|^2 \leq \sum_k |\langle x_k, y \rangle|^2 \leq B\|y\|^2$$

$$\tilde{A}\|y\|^2 \leq \sum_k |\langle \tilde{x}_k, y \rangle|^2 \leq \tilde{B}\|y\|^2$$

✂ Bases that satisfy these constraints are called *Riesz bases*.

✂ If  $A = B$  the frame  $\{x_k\}$  is called a *tight frame*.

- Expansion formula:

$$y = \sum_k \langle x_k, y \rangle \tilde{x}_k = \sum_k \langle \tilde{x}_k, y \rangle x_k$$