

Orthogonal Bases

Monday, January 30, 2017 9:01 AM

A collection of vectors $\{\underline{v}_1, \dots, \underline{v}_N\}$ in a finite-dimensional vector space \mathcal{S} is called an orthogonal basis if

1. $\text{span}(\{\underline{v}_1, \dots, \underline{v}_N\}) = \mathcal{S}$

2. $\underline{v}_j \perp \underline{v}_k$ (i.e. $\langle \underline{v}_j, \underline{v}_k \rangle = 0$) for all $j \neq k \in \{1, \dots, N\}$

if $\|\underline{v}_n\| = 1$ for $n = 1, \dots, N$ then we call it an orthonormal basis or orthobasis

A note on infinite dimensions

if $\mathcal{B} = \{\underline{v}_n\}_{n \in \mathbb{Z}}$ is an infinite sequence of orthonormal vectors, it is an orthobasis of the closure of $\text{span}(\mathcal{B})$.

example: Let $x(t)$ be any function on $[0, 1]$ that is not a polynomial, e.g. $x(t) = \sin(2\pi t)$

Let $\mathcal{B} = \{1, t, t^2, \dots\}$; the span \mathcal{B} is all polynomials on $[0, 1]$. so $x \notin \text{span}(\mathcal{B})$. But we can approximate $x(t)$ arbitrarily well by elements in \mathcal{B} so $x(t) \in \text{closure}(\text{span}(\mathcal{B}))$

Examples of orthobases

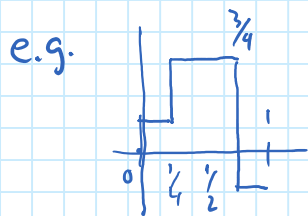
$$\mathcal{S} = \mathbb{R}^2$$

$$\underline{v}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

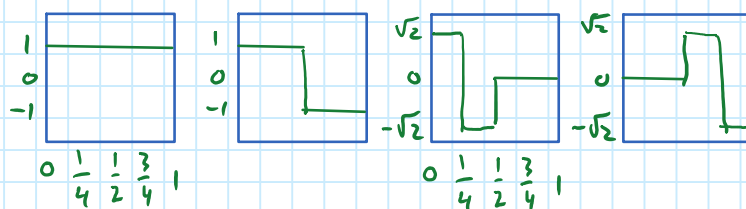
$$\underline{v}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

examples cont.

2. \mathcal{J} = space of piecewise constant functions on $[0, 1/4), [1/4, 1/2), [1/2, 3/4), [3/4, 1]$



The following four functions form an orthobasis



3. Sampling

$\mathcal{B}_{\pi/T}(\mathbb{R})$ = real-valued functions which are band-limited to π/T , equipped with the standard inner product. The set of functions

$$\left\{ \underline{v}_n = \sqrt{T} \frac{\sin(\pi(t-nT)/T)}{\pi(t-nT)}, n \in \mathbb{Z} \right\}$$

is an orthobasis for $\mathcal{B}_{\pi/T}(\mathbb{R})$

$$\left\langle \sqrt{T} \frac{\sin(\pi(t-n_1T)/T)}{\pi(t-n_1T)}, \sqrt{T} \frac{\sin(\pi(t-n_2T)/T)}{\pi(t-n_2T)} \right\rangle$$

$$= \frac{1}{2\pi} \int_{-\pi/T}^{\pi/T} T e^{-j\omega T n_1} e^{j\omega T n_2} d\omega \quad (\text{Parseval})$$

$$= \begin{cases} 1 & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}$$

Linear approximation and orthobases

Wednesday, February 1, 2017 9:37 AM

Best linear approximation problem again:

Given $x \in S$, we want to find the closest point in a subspace T . If T has an orthobasis

$\{\underline{v}_1, \underline{v}_2, \dots, \underline{v}_N\}$ then $\hat{x} = a_1 \underline{v}_1 + a_2 \underline{v}_2 + \dots + a_N \underline{v}_N$

$$\begin{bmatrix} a_1 \\ \vdots \\ a_N \end{bmatrix} = G^{-1} \underline{b} \quad \text{but if } \langle v_i, v_j \rangle = \begin{cases} 1 & i=j \\ 0 & \text{else} \end{cases}$$

Then $G = I$

$$\text{so } \underline{a} = \underline{b} = \begin{bmatrix} \langle x, \underline{v}_1 \rangle \\ \langle x, \underline{v}_2 \rangle \\ \vdots \end{bmatrix}$$

$$\hat{x} = \sum_{n=1}^N \langle x, \underline{v}_n \rangle \underline{v}_n$$

This also works for infinite-dimensional subspaces

$$\underline{x} = \sum_{n=1}^{\infty} \langle \underline{x}, \underline{v}_n \rangle \underline{v}_n$$

Generalizing — any point $\underline{x} \in S$ can be "approximated" perfectly as

$$\underline{x} = \sum_n \langle \underline{x}, \underline{v}_n \rangle \underline{v}_n$$

+transform coefficients.

We can recreate a vector in a Hilbert space from a sequence of numbers $\{\langle x, \underline{v}_n \rangle\}$.

We can think of every different orthobasis of S as a transform and $\{\langle x, \underline{v}_n \rangle\}$ are the transform coefficients

Parseval's Theorem

Wednesday, February 1, 2017 9:49 AM

With respect to the Fourier transform:

$$\|x(t)\|_2^2 = \int_{-\infty}^{\infty} |x(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(j\omega)|^2 d\omega = \frac{1}{2\pi} \|X(j\omega)\|_2^2$$

There is something similar for any orthonormal expansion.

Let \mathcal{S} be a Hilbert space with $\langle \cdot, \cdot \rangle_{\mathcal{S}}$ which induces a norm $\|\cdot\|_{\mathcal{S}}$. Let $\{\underline{v}_k\}_{k \in \Gamma}$ be an orthonormal basis for \mathcal{S} . Then for every $\underline{x}, \underline{y} \in \mathcal{S}$,

$$\langle \underline{x}, \underline{y} \rangle_{\mathcal{S}} = \sum_{k \in \Gamma} \alpha_k \bar{\beta}_k$$

where $\alpha_k = \langle \underline{x}, \underline{v}_k \rangle_{\mathcal{S}}$ and $\beta_k = \langle \underline{y}, \underline{v}_k \rangle_{\mathcal{S}}$

You can think of the α 's and β 's as transform coefficients of \underline{x} & \underline{y} respectively.

so

$$\langle \underline{x}, \underline{y} \rangle_{\mathcal{S}} = \langle \underline{\alpha}, \underline{\beta} \rangle_{\ell_2}$$

$$\|\underline{x}\|_{\mathcal{S}}^2 = \|\underline{\alpha}\|_2^2$$

notice, no $\frac{1}{2\pi}$ factor

Thus, every Hilbert space with an orthonormal basis is equivalent to ℓ_2

— lengths, angles, relations all map to ℓ_2

Proof of Parseval's Theorem

Wednesday, February 1, 2017 10:08 AM

$$\text{Let } \alpha_k = \langle \underline{x}, \underline{v}_k \rangle \quad \text{and} \quad \beta_k = \langle \underline{y}, \underline{v}_k \rangle$$

write

$$\underline{x} = \sum_{k \in \Gamma} \alpha_k \underline{v}_k \quad \text{and} \quad \underline{y} = \sum_{k \in \Gamma} \beta_k \underline{v}_k$$

so

$$\langle \underline{x}, \underline{y} \rangle_S = \left\langle \sum_{k \in \Gamma} \alpha_k \underline{v}_k, \sum_{\ell \in \Gamma} \beta_\ell \underline{v}_\ell \right\rangle_S$$

$$= \sum_{k \in \Gamma} \alpha_k \left\langle \underline{v}_k, \sum_{\ell \in \Gamma} \beta_\ell \underline{v}_\ell \right\rangle_S$$

$$= \sum_{k \in \Gamma} \sum_{\ell \in \Gamma} \alpha_k \bar{\beta}_\ell \langle \underline{v}_k, \underline{v}_\ell \rangle_S$$

for any fixed k , only one term of the inner sum $\neq 0$

$$\langle \underline{x}, \underline{y} \rangle_S = \sum_{k \in \Gamma} \alpha_k \bar{\beta}_k$$

Distances in Hilbert Spaces

Wednesday, February 1, 2017 10:14 AM

$$\| \underline{x} - \underline{y} \|_S = \| \underline{\alpha} - \underline{\beta} \|_2 = \left(\sum_k (\alpha_k - \beta_k)^2 \right)^{1/2}$$

so a small change in a vector in S will yield a small change in the orthobasis expansion coefficients (a.k.a. transform coefficients)

suppose $\{ \alpha_k = \langle \underline{x}, \underline{v}_k \rangle_S \}$ are the transform coefficients of \underline{x}

$$\text{let } \tilde{\alpha}_k = \begin{cases} \alpha_{k_0} + \delta & k = k_0 \\ \alpha_k & k \neq k_0 \end{cases}$$

← localized error
diffused error

$$\text{then } \tilde{\underline{x}} = \sum_k \tilde{\alpha}_k \underline{v}_k$$

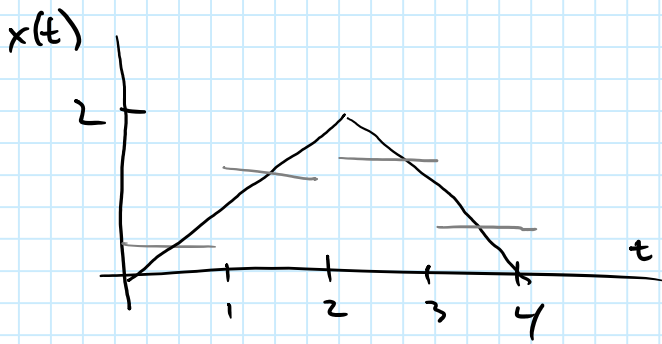
but it's the same

$$\| \underline{x} - \tilde{\underline{x}} \|_S = \| \underline{\alpha} - \tilde{\underline{\alpha}} \|_2 = \delta \quad \text{so } \| \underline{x} - \tilde{\underline{x}} \|_S = \delta$$

This is the distance across the whole signal

Example

Monday, February 6, 2017 9:04 AM



$$x(t) \in L_2([0, 4])$$

$$x(t) = \begin{cases} t & 0 \leq t \leq 2 \\ 4-t & 2 \leq t \leq 4 \end{cases}$$

\mathcal{T} = piecewise constant functions on $[0, 1), [1, 2), [2, 3), [3, 4]$

$$V_n(t) = \begin{cases} 1 & (n-1) \leq t < n \\ 0 & \text{otherwise} \end{cases} \quad n=1, 2, 3, 4$$

$$\sum_n a_n V_n(t)$$

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix} = G^{-1} b$$

Gram matrix

$$b = \begin{bmatrix} \langle x, V_1 \rangle \\ \langle x, V_2 \rangle \\ \vdots \end{bmatrix}$$

$$\langle V_k, V_j \rangle = \int_0^4 V_k V_j(t) dt$$

$$\langle V_1, V_1 \rangle = \int_0^1 1 \cdot 1 dt = 1$$

... orthobasis

$$\langle V_1, V_2 \rangle = \int_0^1 1 \cdot 0 dt + \int_1^2 0 \cdot 1 dt = 0$$

This will be the identity matrix

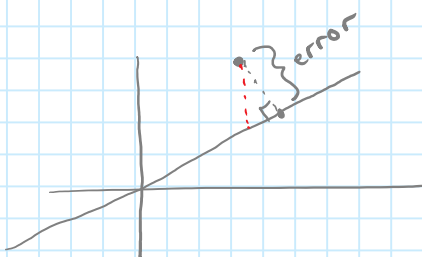
$$a_i = \langle x, V_i \rangle$$

$$a_1 = \langle x, V_1 \rangle = \int_0^1 t dt = \frac{1}{2}$$

$$a_2 = \langle x, V_2 \rangle = \int_1^2 t dt = \frac{4}{2} - \frac{1}{2} = \frac{3}{2}$$

$$a_3 = \langle x, V_3 \rangle = \int_2^3 (4-t) dt = 4 - \left(\frac{9}{2} - \frac{4}{2}\right) = \frac{3}{2}$$

$$a_4 = \langle x, V_4 \rangle = \int_3^4 (4-t) dt = \frac{1}{2}$$



Lengths

Monday, February 6, 2017 9:22 AM

$\{V_k\}$ is an orthobasis on an inner product space

$$x = \sum_k \langle x, v_k \rangle v_k$$

$$\|x\|^2 = \langle x, x \rangle$$

$$= \left\langle \sum_k \langle x, v_k \rangle v_k, \sum_l \langle x, v_l \rangle v_l \right\rangle$$

$$= \sum_k \langle x, v_k \rangle \left\langle v_k, \sum_l \langle x, v_l \rangle v_l \right\rangle$$

$$= \sum_k \langle x, v_k \rangle \sum_l \overline{\langle x, v_l \rangle} \underbrace{\langle v_k, v_l \rangle}_{\begin{cases} 1 & \text{if } k=l \\ 0 & \text{else} \end{cases}}$$

$$= \sum_k \langle x, v_k \rangle \overline{\langle x, v_k \rangle}$$

$$= \sum |\langle x, v_k \rangle|^2$$

Parseval again

Truncating Ortho Expansions

Monday, February 6, 2017 8:40 AM

Say $\{v_k\}_{k=0}^{\infty}$ is an orthonormal basis for a Hilbert space S .

\mathcal{T} is a subspace spanned by the first K elements of $\{v_k\}$

$$\mathcal{T} = \text{span}(\{v_0, v_1, \dots, v_{K-1}\})$$

1) what is the closest point in \mathcal{T} (call it \hat{x}) to a point $x \in S$?

$$\hat{x} = \sum_{k=0}^{K-1} \langle x, v_k \rangle v_k$$

we've already shown this

2) how good is the approximation of \hat{x} to x ?

$$\|x - \hat{x}\|_S^2 = \left\| \sum_{k=0}^{\infty} \langle x, v_k \rangle v_k - \sum_{k=0}^{K-1} \langle x, v_k \rangle v_k \right\|_S^2$$

$$= \left\| \sum_{k=K}^{\infty} \langle x, v_k \rangle v_k \right\|_S^2$$

$$= \sum_{k=K}^{\infty} |\langle x, v_k \rangle|^2$$

if the first K coefficients are much larger than those from K to ∞ , then \hat{x} is a good approximation of x and we can "compress" x using the first K terms.

→ The main idea in video and image compression --- coming up.

Gram-Schmidt

Monday, February 6, 2017 9:39 AM

The goal is to take a sequence of signals $\{v_1, \dots, v_N\}$ and produce $\{u_1, \dots, u_N\}$ such that

$$\text{span}(\{v_1, \dots, v_N\}) = \text{span}(\{u_1, \dots, u_N\})$$

and

$$\langle u_n, u_m \rangle = \begin{cases} 1 & m=n \\ 0 & m \neq n \end{cases}$$

Assume $\{v_n\}$ forms a basis for an N -dimensional space or subspace.

1) choose $w_1 = v_1$ and normalize it to get

$$u_1 = \frac{w_1}{\|w_1\|}$$

2) To get u_2 , we subtract from v_2 its projection onto u_1 .

$$w_2 = v_2 - \langle v_2, u_1 \rangle u_1$$

$$u_2 = \frac{w_2}{\|w_2\|}$$

$$\langle u_2, u_1 \rangle = \frac{1}{\|w_2\|} \langle w_2, u_1 \rangle$$

$$= \frac{1}{\|w_2\|} (\langle v_2, u_1 \rangle - \langle v_2, u_1 \rangle \langle u_1, u_1 \rangle)$$

$$= 0$$

so $\{u_1, u_2\}$ is an orthonormal basis for $\text{span}(\{v_1, v_2\})$

Gram-Schmidt II

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3) At the beginning of the k^{th} step, $\{u_1, \dots, u_{k-1}\}$ is an orthobasis for $\text{span}(\{v_1, \dots, v_{k-1}\})$.

So we u_k by subtracting the projection of v_k onto the $\text{span}(\{u_1, \dots, u_{k-1}\})$ and normalizing:

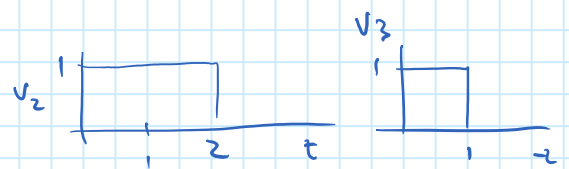
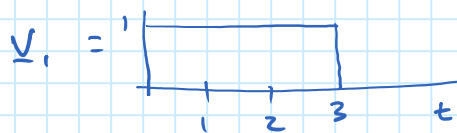
$$w_k = v_k - \sum_{l=1}^{k-1} \langle v_k, u_l \rangle u_l$$

$$u_k = \frac{w_k}{\|w_k\|}$$

By induction, $\{u_1, \dots, u_k\}$ is an orthobasis for $\text{span}(\{v_1, \dots, v_k\})$

If, at any point, $w_k = 0$, then the set $\{v_k\}$ was not a basis — just toss that vector and continue.

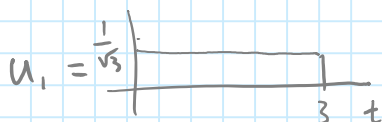
Example: Let \mathcal{J} be the set of piecewise-constant signals on $[0, 1)$, $[1, 2)$, $[2, 3]$ with the standard inner product, L_2



$$w_1 = v_1$$

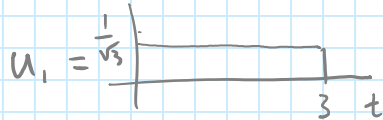
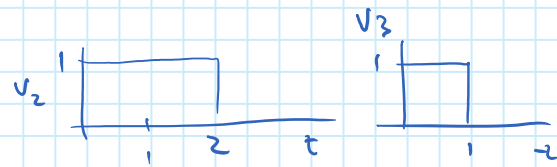
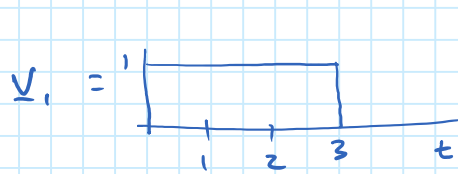
$$u_1 = \frac{w_1}{\|w_1\|}$$

$$\|w_1\| = \sqrt{\langle w_1, w_1 \rangle} = \left(\int_0^3 1 \cdot 1 dt \right) = \sqrt{3}$$



Gram-Schmidt example continued

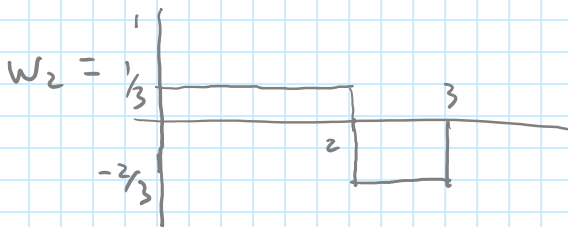
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$$\langle v_2, u_1 \rangle = \int_0^2 \frac{1}{\sqrt{3}} dt = \frac{2}{\sqrt{3}}$$

$$w_2 = v_2 - \langle v_2, u_1 \rangle u_1$$

$$\langle v_2, u_1 \rangle u_1 = \frac{2}{3} \quad \text{for } t \in [0, 2]$$



$$\|w_2\|^2 = \frac{2}{9} + \frac{4}{9} = \frac{6}{9} = \frac{2}{3}$$

$$\|w_2\| = \sqrt{\frac{2}{3}}$$

$$u_2 = \begin{cases} \frac{1}{\sqrt{6}} & 0 \leq t < 2 \\ -\frac{2}{\sqrt{6}} & 2 \leq t < 3 \\ 0 & \text{elsewhere} \end{cases}$$

$$\langle v_3, u_1 \rangle = \frac{1}{\sqrt{3}}$$

$$\langle v_3, u_2 \rangle = \frac{1}{3}$$

$$w_3 = v_3 - \langle v_3, u_1 \rangle u_1 - \langle v_3, u_2 \rangle u_2$$

$$= \begin{cases} 1 - \frac{1}{3} - \frac{1}{9} = \frac{5}{9} & 0 \leq t < 1 \\ -\frac{1}{3} - \frac{1}{9} = -\frac{4}{9} & 1 \leq t < 2 \\ -\frac{1}{3} + \frac{2}{9} = -\frac{1}{9} & 2 \leq t \leq 3 \end{cases}$$

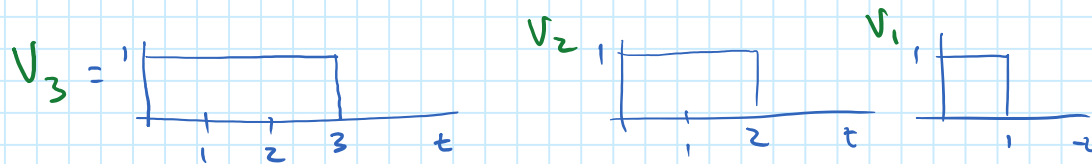
$$u_3 = \frac{w_3}{\|w_3\|}$$

$$\|w_3\|^2 = \frac{25}{81} + \frac{16}{81} + \frac{1}{81} = \frac{42}{81} = \frac{14}{27}$$

$$u_3 = \sqrt{\frac{27}{14}} \cdot w_3 = \frac{3\sqrt{3}}{\sqrt{14}} w_3 = \begin{cases} \frac{5\sqrt{42}}{14} & 0 \leq t < 1 \\ -\frac{4\sqrt{42}}{14} & 1 \leq t < 2 \\ -\frac{\sqrt{42}}{14} & 2 \leq t \leq 3 \end{cases}$$

Gram-Schmidt example 2


Monday, February 6, 2017 10:19 AM



Start at the other end...

$$u_1 = V_1$$

$W_2 =$  $\Rightarrow u_2 = W_2$

$W_3 =$  $\Rightarrow u_3 = W_3$