

## Orthogonal and Orthonormal Bases

A set  $S = \{v_1, v_2, \dots, v_n\}$  is an orthogonal basis for  $V$  if

(i)  $S$  is a basis for  $V$

(ii)  $\langle v_i, v_j \rangle = 0 \quad i \neq j$

The latter says that  $v_k$  are mutually orthogonal. Generally speaking  $\|v_k\| \neq 1$  but if

(iii)  $\langle v_i, v_i \rangle = 1 \quad \forall i = 1, 2, \dots, n$

the set is said to be an orthonormal basis.

EXAMPLE  $V = \mathbb{R}^3$  orthonormal basis

$$S = \left\{ (0, 1, 0), \left(\frac{1}{\sqrt{2}}, 0, -\frac{1}{\sqrt{2}}\right), \left(\frac{1}{\sqrt{2}}, 0, \frac{1}{\sqrt{2}}\right) \right\} = \{v_1, v_2, v_3\}$$

mutually orthogonal under Euclidean inner product

EXAMPLE  $V = P_1$  orthonormal basis

$$S = \left\{ 1, \sqrt{12} \left(\frac{1}{2} - x\right) \right\} = \{v_1, v_2\}$$

using  $\langle u, v \rangle = \int_0^1 u(x)v(x)dx.$

$$\langle v_1, v_1 \rangle = \int_0^1 1^2 dx = 1$$

$$\langle v_1, v_2 \rangle = \int_0^1 \sqrt{12} \left(\frac{1}{2} - x\right) dx = \frac{1}{24} \left(\frac{1}{2} - x\right)^2 \Big|_0^1 = 0$$

and can verify  $\langle v_2, v_2 \rangle = 1.$

EXAMPLE  $V = M_{22}$        $\langle u, v \rangle = \text{Tr}(u^T v)$

Consider the subset of symmetric matrices

$$W = \{ w \in V : w^T = w \}$$

The following is an orthogonal basis for  $W$

$$S = \{ v_1, v_2, v_3 \} = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

It is not an orthonormal basis, since,

$$\langle v_2, v_2 \rangle = 2$$

## Expansions and Orthogonal Coordinates.

Throughout,  $S = \{v_1, \dots, v_n\}$  will be an orthogonal basis for  $V$ . Then for any  $v \in V$  there are constants  $\alpha_1, \dots, \alpha_n$  such that

$$(1) \quad v = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n$$

Thus, the coordinate of  $v$  relative to  $S$  is

$$(2) \quad (v)_S = (\alpha_1, \dots, \alpha_n)$$

Normally finding  $\alpha_k$  involves solving an  $n$  by  $n$  system. But we can exploit the orthogonality of  $v_k$  to greatly reduce the amount of work to find  $(v)_S$ .

Take the inner product of  $v$  with  $v_k$

$$\langle v, v_k \rangle = \alpha_1 \underbrace{\langle v_1, v_k \rangle}_0 + \dots + \alpha_k \underbrace{\langle v_k, v_k \rangle}_{\neq 0} + \dots + \alpha_n \underbrace{\langle v_n, v_k \rangle}_0$$

Only the  $k^{\text{th}}$  term is nonzero. Thus

$$\alpha_k = \frac{\langle v, v_k \rangle}{\langle v_k, v_k \rangle} = \frac{\langle v, v_k \rangle}{\|v_k\|^2}$$

and

$$v = \frac{\langle v, v_1 \rangle}{\|v_1\|^2} v_1 + \dots + \frac{\langle v, v_n \rangle}{\|v_n\|^2} v_n$$

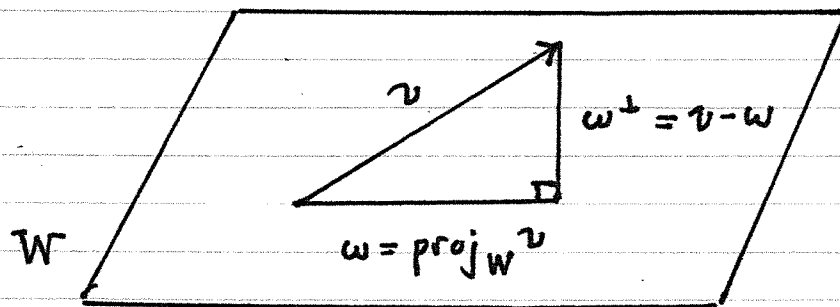
## Projections

Let  $W$  be a subspace of  $V$  with orthonormal basis

$$S = \{v_1, v_2, \dots, v_n\}$$

so that  $W = \text{span}(S) \subset V$ . Then, we define the projection of  $v \in V$  onto  $W$  by

$$(1) \quad w = \text{proj}_W v = \langle v, v_1 \rangle v_1 + \langle v, v_2 \rangle v_2 + \dots + \langle v, v_n \rangle v_n$$



In what sense is this picture true given (1)?  
One would expect  $v - w \in W^\perp$ . We can verify this to be true:

$$\begin{aligned} \langle w - v, v_k \rangle &= \sum_{i=1}^n \langle v, v_i \rangle \overset{0 \text{ if } i \neq k}{\langle v_i, v_k \rangle} - \langle v, v_k \rangle \\ &= \langle v, v_k \rangle \cdot 1 - \langle v, v_k \rangle \\ &= 0 \quad \square \end{aligned}$$

## Projection Theorem

Let  $W$  be a finite dimensional subspace of inner product space  $V$ . Then every  $v \in V$  can be expressed as a sum

$$v = w + w^\perp$$

where  $w \in W$ ,  $w^\perp \in W^\perp$ .

Pf: Let  $S = \{v_1, \dots, v_n\}$  be an orthonormal basis of  $W$ . By previous discussion

$$w = \text{proj}_W v \in W$$

$$w^\perp = v - w \in W^\perp \quad \square$$

## Normalized versus non normalized

It is more common to work with non-normalized (orthogonal) vectors.

Suppose  $S = \{v_1, \dots, v_n\}$  is not normalized. Then

$$\text{proj}_W v = \frac{\langle v, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 + \dots + \frac{\langle v, v_n \rangle}{\langle v_n, v_n \rangle} v_n$$

versus

$$\text{proj}_W v = \langle v, \hat{v}_1 \rangle \hat{v}_1 + \dots + \langle v, \hat{v}_n \rangle \hat{v}_n$$

if the  $\hat{v}_k$  are normalized,  $\|\hat{v}_k\| = 1$ .

EXAMPLE  $V = \mathbb{R}^4$ ,  $W = \text{span}\{v_1\} = \text{span}\{(1, 1, 0, -2)\}$

Find the orthogonal decomposition of  $v = (2, 1, 3, 4)$  relative to  $W$ :

$$(1) \quad v = w + w^\perp \quad w \in W \quad w^\perp \in W^\perp$$

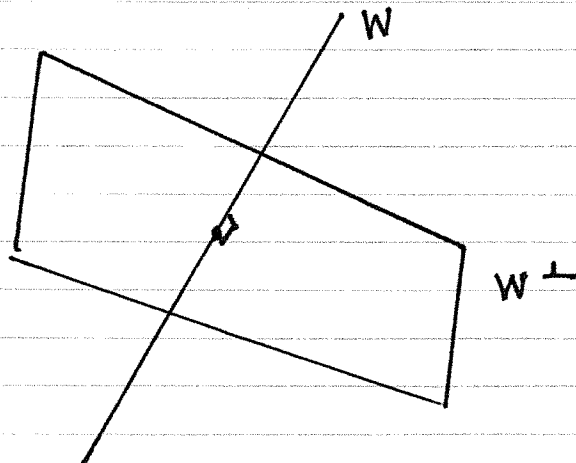
First we find  $w$

$$w = \text{proj}_W v = \frac{\langle v, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 = -\frac{5}{6} v_1 = -\frac{5}{6} (1, 1, 0, -2)$$

Then from (1)

$$w^\perp = v - w = \frac{1}{6} (17, 11, 18, 14)$$

One can verify  $\langle w, w^\perp \rangle = 0$ .



EXAMPLE  $V = M_{22}$ ,  $\langle u, v \rangle \equiv \text{Tr}(u^T v)$

$$W = \text{span}\{v_1\} = \text{span}\left\{\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}\right\} \quad v \equiv \begin{bmatrix} 2 & 1 \\ -1 & 1 \end{bmatrix}$$

Pre calculate inner products for projection

$$\langle v, v_1 \rangle = 4$$

$$\langle v_1, v_1 \rangle = 3$$

Thus

$$w = \text{proj}_W v = \frac{\langle v, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 = \frac{4}{3} v_1$$

To summarize

$$w = \begin{bmatrix} 4/3 & 4/3 \\ 0 & 4/3 \end{bmatrix}$$

$$w^\perp = v - w = \begin{bmatrix} 2/3 & -1/3 \\ -1 & -1/3 \end{bmatrix}$$

EXAMPLE  $V = M_{22}$       $\langle u, v \rangle = \text{Tr}(u^T v)$

Given  $W$  in terms of orthogonal basis:

$$W = \text{span}\{w_1, w_2\} = \text{span}\left\{ \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix}, \begin{bmatrix} -2 & 0 \\ 1 & -2 \end{bmatrix} \right\}$$

Easy to check  $\langle w_1, w_2 \rangle = 0$ . Let

$$v = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix}$$

Compute projection of  $v$  onto  $W$

$$\begin{aligned} (1) \quad w &= \text{proj}_W v = \frac{\langle v, w_1 \rangle}{\langle w_1, w_1 \rangle} w_1 + \frac{\langle v, w_2 \rangle}{\langle w_2, w_2 \rangle} w_2 \\ &= \frac{6}{6} w_1 + \frac{(-2)}{9} w_2 \\ &= w_1 - \frac{2}{9} w_2 \\ &= \begin{bmatrix} 13/9 & 2 \\ -2/9 & -5/9 \end{bmatrix} \end{aligned}$$

Then the orthogonal decomposition is

$$v = w + w^\perp$$

where  $w^\perp$  can be computed (knowing (1))

$$w^\perp = v - w$$



EXAMPLE  $V = \mathbb{R}^3$   $W = \{x \in \mathbb{R}^3 : x_1 + x_2 + x_3 = 0\}$

To carry out a projection calculation we need an orthogonal basis. In general we use Gram-Schmidt process (next section) to find one. We postpone this discussion until later and note:

$$W = \text{span}\{w_1, w_2\} = \text{span}\left\{\frac{1}{\sqrt{2}}(1, 0, -1), \frac{1}{\sqrt{6}}(1, -2, 1)\right\}$$

Can easily verify  $\langle w_1, w_2 \rangle = 0$  and  $w_i \in W$ ,  $\|w_i\| = 1$ .

For  $v = (1, 1, -1)$  we can compute

$$\begin{aligned} (1) \quad w &= \text{proj}_W v = \langle v, w_1 \rangle w_1 + \langle v, w_2 \rangle w_2 \\ &= \sqrt{2} w_1 - \frac{1}{3} \sqrt{6} w_2 \\ &= \left(\frac{2}{3}, \frac{2}{3}, -\frac{4}{3}\right) \end{aligned}$$

Then the orthogonal decomposition

$$v = w + w^\perp$$

is completed by calculating

$$(2) \quad w^\perp = v - w = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$$

It is easily verified  $\langle w, w^\perp \rangle = 0$ .

## Projections in $\mathbb{R}^n$ as Linear Transformations

Let  $V = \mathbb{R}^n$  and  $S = \{w_1, \dots, w_n\}$  be an orthogonal basis (in  $V$ ) for

$$W = \text{span}\{w_1, \dots, w_n\}$$

Then for any  $v \in V$

$$T(v) = \text{proj}_W v = \frac{\langle v, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 + \dots + \frac{\langle v, v_n \rangle}{\langle v_n, v_n \rangle} v_n$$

It is readily verified

$$(1) \quad T: \mathbb{R}^n \rightarrow \mathbb{R}^n$$

$$(2) \quad T(kv) = kT(v) \quad \forall k \in \mathbb{R}$$

$$(3) \quad T(v_1 + v_2) = T(v_1) + T(v_2) \quad \forall v_k \in \mathbb{R}^n$$

That is to say the operation of projection is linear and since  $V = \mathbb{R}^n$  there exists a matrix such that

$$T(v) = Av$$

In particular, if  $e_k$  are standard basis,

$$A = [T(e_1) \dots T(e_n)]$$

EXAMPLE  $V = \mathbb{R}^3$      $W = \{x \in \mathbb{R}^3 : x_1 + x_2 + x_3 = 0\}$

As discussed before

$$W = \text{span}\{v_1, v_2\} \quad v_1 = \frac{1}{\sqrt{2}}(1, 0, -1) \quad v_2 = \frac{1}{\sqrt{6}}(1, -2, 1)$$

Then  $T: \mathbb{R}^3 \rightarrow \mathbb{R}^3$  projection operator is

$$T(v) = \text{proj}_W v = \langle v, v_1 \rangle v_1 + \langle v, v_2 \rangle v_2$$

where  $T(v) = Av$ ,  $A = [T(e_1) \ T(e_2) \ T(e_3)]$ .

$$T(e_1) = \text{proj}_W e_1 = \frac{1}{\sqrt{2}} v_1 + \frac{1}{\sqrt{6}} v_2 = \left(\frac{2}{3}, -\frac{1}{3}, -\frac{1}{3}\right)$$

$$T(e_2) = \text{proj}_W e_2 = 0 v_1 - \frac{\sqrt{6}}{3} v_2 = \left(-\frac{1}{3}, \frac{2}{3}, -\frac{1}{3}\right)$$

$$T(e_3) = \text{proj}_W e_3 = -\frac{1}{\sqrt{2}} v_1 + \frac{1}{\sqrt{6}} v_2 = \left(-\frac{1}{3}, -\frac{1}{3}, \frac{2}{3}\right)$$

Compiling the results

$$T(v) = Av = \frac{1}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} v$$

Remark: If one used a different basis (orthog) for  $W$  the resulting  $A$  would be the same. Hard to prove.

## Gram-Schmidt Orthogonalization

Every finite dimensional inner product space has an orthonormal basis.

$$S = \{u_1, u_2, \dots, u_n\} \quad \text{basis}$$

$$S_{\perp} = \{v_1, v_2, \dots, v_n\} \quad \text{orthogonal basis.}$$

Given  $S$  the basis  $S_{\perp}$  is found using the following Algorithm

$$(1) \quad v_1 = u_1 \quad W_1 = \text{span}\{v_1\}$$

$$(2) \quad v_2 = u_2 - \text{proj}_{W_1} u_2 \quad W_2 = \text{span}\{v_1, v_2\}$$

$$(3) \quad v_k = u_k - \text{proj}_{W_{k-1}} u_k \quad W_k = \text{span}\{v_1, \dots, v_k\}$$

Proof: Inductive (Text)

EXAMPLE  $S = \{1, x, x^2\}$   $V = P_2$   $\langle u, v \rangle = \int_0^1 u(x)v(x)dx$

$$v_1 = u_1 = 1$$

$$v_2 = u_2 - \frac{\langle u_2, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 = u_2 - \frac{\frac{1}{2}}{1} v_1 = x - \frac{1}{2}$$

$$v_3 = u_3 - \frac{\langle u_3, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1 - \frac{\langle u_3, v_2 \rangle}{\langle v_2, v_2 \rangle} v_2 = \dots = x^2 - x + \frac{1}{6}$$

Thus

$$S_{\perp} = \left\{ 1, x - \frac{1}{2}, x^2 - x + \frac{1}{6} \right\}$$