6.3 Orthogonal Projections

Suppose $\mathbf{u}, \mathbf{v} \in V$. We would like to write \mathbf{u} as a scalar multiple of \mathbf{v} plus a vector \mathbf{w} orthogonal to \mathbf{v} . To discover how to write \mathbf{u} as a scalar multiple of \mathbf{v} plus a vector orthogonal to \mathbf{v} , let $a \in \mathbb{R}$ denote a scalar. Then

$$\mathbf{u} = a\mathbf{v} + (\mathbf{u} - a\mathbf{v}).$$

Thus we need to choose a so that \mathbf{v} is orthogonal to $(\mathbf{u} - a\mathbf{v})$. In other words, we want

$$0 = \langle \mathbf{u} - a\mathbf{v}, \mathbf{v} \rangle = \langle \mathbf{u}, \mathbf{v} \rangle - a \|\mathbf{v}\|^2.$$

The equation above shows that we should choose a to be $\langle \mathbf{u}, \mathbf{v} \rangle / \|\mathbf{v}\|^2$, provided that $\mathbf{v} \neq \mathbf{0}$. Making this choice of a, we can write

$$\mathbf{u} = \frac{\langle \mathbf{u}, \mathbf{v} \rangle}{\|\mathbf{v}\|^2} \mathbf{v} + \left(\mathbf{u} - \frac{\langle \mathbf{u}, \mathbf{v} \rangle}{\|\mathbf{v}\|^2} \mathbf{v} \right). \tag{1}$$

It is easy to verify that the equation above writes \mathbf{u} as a scalar multiple of \mathbf{v} plus a vector orthogonal to \mathbf{v} . Suppose U is a subspace of V. Each vector $\mathbf{v} \in V$ can be written uniquely in the form

$$\mathbf{v} = \mathbf{u} + \mathbf{w}$$

where $\mathbf{u} \in U$ and $\mathbf{w} \in U^{\perp}$. We use this decomposition to define an operator on V, denoted P_U (in the textbook, proj_U), called the *orthogonal projection* of V onto U. For $\mathbf{v} \in V$, we define $P_U\mathbf{v}$ to be the vector \mathbf{u} in the decomposition above.

It is easy to verify that P_U is an operator that has the following properties:

- range $P_U = U$;
- null $P_U = U^{\perp}$;
- $\mathbf{v} P_U \mathbf{v} \in U^{\perp}$ for every $\mathbf{v} \in V$;
- $P_U^2 = P_U$;
- $||P_U\mathbf{v}|| \le ||\mathbf{v}||$ for every $\mathbf{v} \in V$.

Theorem 8 (The Orthogonal Decomposition Theorem). Let W be a subspace of V. Then each $\mathbf{y} \in V$ can be written uniquely in the form

$$\mathbf{y} = \hat{\mathbf{y}} + \mathbf{z} \tag{2}$$

where $\hat{\mathbf{y}}$ is in W and \mathbf{z} is in W^{\perp} . In fact, if $\{\mathbf{u}_1,\ldots,\mathbf{u}_p\}$ is any orthogonal basis for W, then

$$\hat{\mathbf{y}} = \frac{\langle \mathbf{y}, \mathbf{u}_1 \rangle}{\langle \mathbf{u}_1, \mathbf{u}_1 \rangle} \mathbf{u}_1 + \dots + \frac{\langle \mathbf{y}, \mathbf{u}_p \rangle}{\langle \mathbf{u}_p, \mathbf{u}_p \rangle} \mathbf{u}_p$$
(3)

and $\mathbf{z} = \mathbf{y} - \hat{\mathbf{y}}$.

If $\mathbf{y} \in W = \operatorname{Span}\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$, then $P_W \mathbf{y} = \mathbf{y}$. Furthermore, if $\{\mathbf{e}_1, \dots, \mathbf{e}_m\}$ is an orthonormal basis of W, then

$$P_W \mathbf{y} = \langle \mathbf{y}, \mathbf{e}_1 \rangle \mathbf{e}_1 + \dots + \langle \mathbf{y}, \mathbf{e}_m \rangle \mathbf{e}_m \tag{4}$$

for every $\mathbf{y} \in V$.

Theorem 9 (The Best Approximation Theorem). Suppose U is a subspace of V and $\mathbf{v} \in V$. Then

$$\|\mathbf{v} - P_U \mathbf{v}\| < \|\mathbf{v} - \mathbf{u}\|$$

for every $\mathbf{u} \in U$. Furthermore, if $\mathbf{u} \in U$ and the inequality above is an equality, then $\mathbf{u} = P_U \mathbf{v}$.

In other words, P_U **v** is the closest point in U to **v**. The vector P_U **v** is called the best approximation to **v** by elements of U.

Proof. Suppose $\mathbf{u} \in U$. Then

$$\|\mathbf{v} - P_U \mathbf{v}\|^2 \le \|\mathbf{v} - P_U \mathbf{v}\|^2 + \|P_U \mathbf{v} - \mathbf{u}\|^2 \tag{5}$$

$$= \|(\mathbf{v} - P_U \mathbf{v}) + (P_U \mathbf{v} - \mathbf{u})\|^2 \tag{6}$$

$$= \|\mathbf{v} - \mathbf{u}\|^2,\tag{7}$$

where (5) comes from the Pythagorean Theorem, which applies because $\mathbf{v} - P_U \mathbf{v} \in U^{\perp}$ and $P_U \mathbf{v} - \mathbf{u} \in U$. Taking square roots give the desired inequality.

Our inequality is an equality if and only if (4) is an equality, which happens if and only if $||P_U\mathbf{v} - \mathbf{u}|| = 0$, which happens if and only if $\mathbf{u} = P_U\mathbf{v}$.

The Best Approximation theorem is often combined with the formula (4) to compute explicit solutions to minimization problems.

Theorem 10. If $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ is an orthonormal basis for a subspace W of \mathbb{R}^n , then If $U = [\mathbf{u}_1 \cdots \mathbf{u}_p]$, then

$$P_W \mathbf{y} = UU^T \mathbf{y} \quad \text{for all } \mathbf{y} \in \mathbb{R}^n.$$
 (8)

Example 1. Let
$$W = \text{Span}\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\}$$
 where $\mathbf{u}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ -1 \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \mathbf{u}_3 = \begin{bmatrix} 0 \\ -1 \\ 1 \\ -1 \end{bmatrix}$. Write $\mathbf{y} = \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \mathbf{u}_3 \end{bmatrix}$.

$$\begin{bmatrix} 3 \\ 4 \\ 5 \\ 6 \end{bmatrix}$$
 as the sum of a vector in W and a vector orthogonal to W.

Example 2. Find the closest point to
$$\mathbf{y} = \begin{bmatrix} 3 \\ -1 \\ 1 \\ 13 \end{bmatrix}$$
 in the subspace W spanned by $\mathbf{v}_1 = \begin{bmatrix} 1 \\ -2 \\ -1 \\ 2 \end{bmatrix}$ and

$$\mathbf{v}_2 = \begin{bmatrix} -4 \\ 1 \\ 0 \\ 3 \end{bmatrix}.$$