Recall:

1) The least square solutions of a matrix equation $A\mathbf{x} = \mathbf{b}$ are the solutions of the equation

$$A\mathbf{x} = \mathrm{proj}_{\mathrm{Col}(A)}\mathbf{b}$$

2) If $A\mathbf{x} = \mathbf{b}$ is a consistent equation, then $\mathbf{b} \in \mathrm{Col}(A)$, and $\mathrm{proj}_{\mathrm{Col}(A)}\mathbf{b} = \mathbf{b}$. In such case the least square solutions of $A\mathbf{x} = \mathbf{b}$ are just the ordinary solutions.

3) If $A\mathbf{x} = \mathbf{b}$ is inconsistent, then the least square solutions are the best substitute for the (nonexistent) ordinary solutions.

4) If $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is an orthogonal basis of a subspace V of $\mathbb{R}^n$ then

$$\mathrm{proj}_V\mathbf{w} = \left(\frac{\mathbf{w}\cdot\mathbf{v}_1}{\mathbf{v}_1\cdot\mathbf{v}_1}\right)\mathbf{v}_1 + \dots + \left(\frac{\mathbf{w}\cdot\mathbf{v}_k}{\mathbf{v}_k\cdot\mathbf{v}_k}\right)\mathbf{v}_k$$

5) If $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is an arbitrary basis of V then we can use the Gram-Schmidt process to obtain an orthogonal basis of V.

How to compute least square solutions of $A\mathbf{x} = \mathbf{b}$
(version 1.0)

1) Compute a basis of $\mathrm{Col}(A)$.

2) Use the Gram-Schmidt process to get an orthogonal basis of $\mathrm{Col}(A)$.

3) Use the orthogonal basis to compute $\mathrm{proj}_{\mathrm{Col}(A)}\mathbf{b}$.

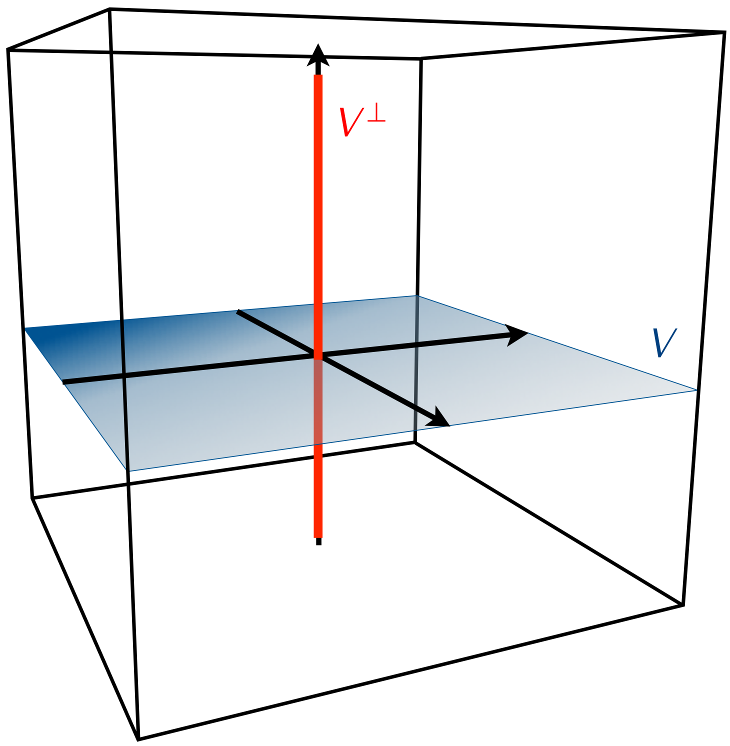
4) Compute solutions of the equation $A\mathbf{x} = \mathrm{proj}_{\mathrm{Col}(A)}\mathbf{b}$.

Next goal: Simplify this.

Definition

If V is a subspace of $\mathbb{R}^n$ then the *orthogonal complement* of V is the set $V^\perp$ of all vectors orthogonal to V:

$$V^\perp = \{\mathbf{w} \in \mathbb{R}^n \mid \mathbf{w} \cdot \mathbf{v} = 0 \text{ for all } \mathbf{v} \in V\}$$



Proposition

If V is a subspace of $\mathbb{R}^n$ then:

1) $V^\perp$ is also a subspace of $\mathbb{R}^n$.

2) For $\mathbf{w} \in \mathbb{R}^n$, the projection $\mathrm{proj}_V \mathbf{w}$ is the unique vector such that $\mathrm{proj}_V \mathbf{w} \in V$ and $\mathbf{w} - \mathrm{proj}_V \mathbf{w} \in V^\perp$.

Definition

If A is an $m \times n$ matrix then the *row space* of A is the subspace $\mathrm{Row}(A)$ of $\mathbb{R}^n$ spanned by rows of A.

Example

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$$

Proposition

If A is a matrix then
$$\mathrm{Row}(A)^\perp = \mathrm{Nul}(A)$$

Corollary

If A is a matrix then

$$\mathrm{Col}(A)^{\perp} = \mathrm{Nul}(A^T)$$

Back to least square solutions

Theorem

A vector $\hat{\mathbf{x}}$ is a least square solution of a matrix equation

$$A\mathbf{x} = \mathbf{b}$$

if and only if $\hat{\mathbf{x}}$ is an ordinary solution of the equation

$$(A^T A)\mathbf{x} = A^T\mathbf{b}$$

Definition

The equation

$$(A^T A)\mathbf{x} = A^T\mathbf{b}$$

is called the *normal equation* of $A\mathbf{x} = \mathbf{b}$.

How to compute least square solutions of $A\mathbf{x} = \mathbf{b}$

(version 2.0)

1) Compute $A^T A$, $A^T\mathbf{b}$.

2) Solve the normal equation $(A^T A)\mathbf{x} = A^T\mathbf{b}$.

Example. Compute least square solutions of the following equation:

$$\begin{bmatrix} 1 & 1 \\ 0 & 2 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$