

$$A \quad n \times m \quad A: \mathbb{R}^m \rightarrow \mathbb{R}^n$$

$$A^T \quad m \times n \quad A^T: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

$$A^T A: \mathbb{R}^m \rightarrow \mathbb{R}^m$$

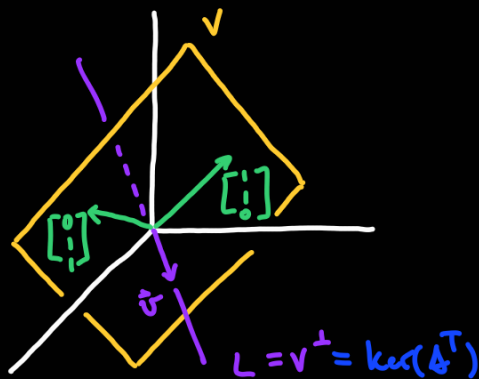
$$(MN)^T = N^T M^T$$

$$(\text{im}(A))^\perp = \text{ker}(A^T)$$

Example: $T: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ projection onto $V = \text{span}\left(\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}\right)$.

$$A = \begin{bmatrix} 2/3 & 1/3 & -1/3 \\ 1/3 & 2/3 & 1/3 \\ -1/3 & 1/3 & 2/3 \end{bmatrix}$$

$$A^T = A$$



$\text{im}(A)$ is the plane $x - y + z = 0$

$$\vec{v} = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

$$\text{im}(A) = V$$

$$V^\perp = L$$

So to have $\text{ker}(A^T) = (\text{im}(A))^\perp = V^\perp = L$.

To compute $\text{ker}(A^T)$ we solve $A^T \vec{x} = \vec{0}$:

$$\begin{bmatrix} 2/3 & 1/3 & -1/3 \\ 1/3 & 2/3 & 1/3 \\ -1/3 & 1/3 & 2/3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

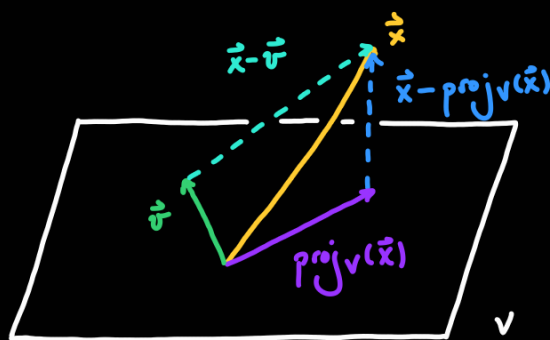
$$\vec{x} = t \cdot \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} = t \cdot \vec{v}$$

So $\text{ker}(A^T) = \text{span}(\vec{v}) = L = (\text{im}(A))^\perp$.

$$\mathbb{R}^3 \quad \dim(\text{im}(A)) = 2$$

$$\mathbb{R}^n \quad \dim(\text{im}(A)) = n-1$$

Review:



$$\|x - \text{proj}_V(x)\|$$

$$\|x - v\|$$

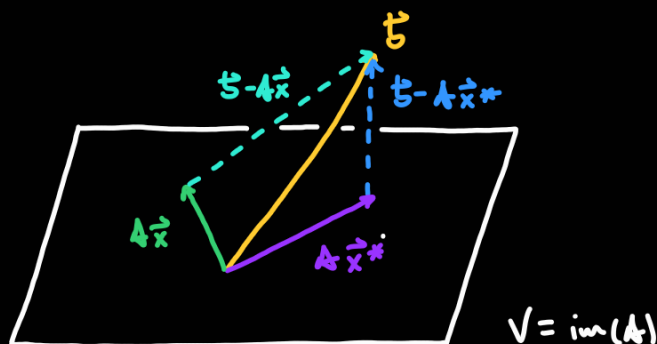
The orthogonal projection onto a subspace V is solving a minimization problem:

it looks at all the distances $\|x - v\|$ for v in V , and chooses the smallest.

$$\|x - \text{proj}_V(x)\| \leq \|x - v\| \quad \text{for } v \text{ in } V$$

Suppose we are given $Ax = b$, A is an $n \times m$ matrix, b vector in \mathbb{R}^n .

$$b - Ax = 0$$



We call x^* a least-squares solution of the system if $\|b - Ax^*\| \leq \|b - Ax\|$ for any

other x in \mathbb{R}^m .

Note that from $Ax = b$ we can get $A^T Ax = A^T b$, which is always a consistent

system. This equation is called the normal equation of the system.

Theorem: If A ($n \times n$) has kernel $\{0\}$ then the system $A\vec{x} = \vec{b}$ has exactly

one least-squares solution: $\vec{x}^* = \underbrace{(A^T A)^{-1}}_{A^{-1} (A^T)^{-1}} A^T \vec{b}$.

(If A orthogonal then $A^T A = I_n$. } as a matrix

Example: $T: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ projection onto $V = \text{span}\left(\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}\right)$

$$P = \begin{bmatrix} 2/3 & 1/3 & -1/3 \\ 1/3 & 2/3 & 1/3 \\ -1/3 & 1/3 & 2/3 \end{bmatrix}$$

A has two linearly independent columns, so $\text{ker}(A) = \{0\}$.

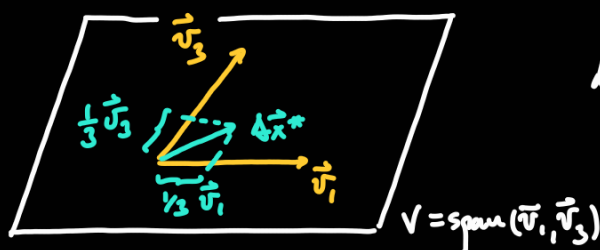
Find the least squares solution of $A\vec{x} = \vec{b}$ for $A = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$:

(we want $V = \text{im}(A)$, and $\text{im}(A)$ is the span of its columns)

$$\begin{aligned} \vec{x}^* &= (A^T A)^{-1} A^T \vec{b} = \left(\begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \\ &= \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{aligned}$$

"decomposing \vec{x}^* into $\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ "

$$\text{im}(A) = \text{span}\left(\underbrace{\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}}_{\vec{v}_1}, \underbrace{\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}}_{\vec{v}_3}\right)$$



$$\begin{aligned} A\vec{x}^* &= \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \frac{1}{3} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \\ &= \frac{1}{3} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} = \frac{1}{3} \vec{v}_1 + \frac{1}{3} \vec{v}_3 \end{aligned}$$

$$\text{proj}_V(\vec{v}_2) = \frac{1}{3} \vec{v}_1 + \frac{1}{3} \vec{v}_3 \quad \vec{v}_2 = \vec{b} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

Theorem: V be a subspace of \mathbb{R}^n with basis $\vec{v}_1, \dots, \vec{v}_m$, the matrix associated

to the orthogonal projection onto V is:

$$P = A(A^T A)^{-1} A^T = \begin{bmatrix} | & & | \\ \frac{1}{\sqrt{1}} & \dots & \frac{1}{\sqrt{m}} \\ | & & | \end{bmatrix} \left(\begin{bmatrix} - & \frac{1}{\sqrt{1}} & - \\ \vdots & \vdots & \vdots \\ - & \frac{1}{\sqrt{m}} & - \end{bmatrix} \begin{bmatrix} | & & | \\ \frac{1}{\sqrt{1}} & \dots & \frac{1}{\sqrt{m}} \\ | & & | \end{bmatrix} \right)^{-1} \begin{bmatrix} - & \frac{1}{\sqrt{1}} & - \\ \vdots & \vdots & \vdots \\ - & \frac{1}{\sqrt{m}} & - \end{bmatrix}.$$

Do this with $V = \text{span} \left(\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right)$.

$$P = \begin{bmatrix} 2/3 & 1/3 & -1/3 \\ 1/3 & 2/3 & 1/3 \\ -1/3 & 1/3 & 2/3 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix}$$

true by the Theorem

$$P = A(A^T A)^{-1} A^T$$