

Orthonormal sets

$$S \subseteq \mathbb{R}^k \text{ s.t. } (\varphi, \psi) = \begin{cases} 0 & \text{if } \varphi \neq \psi \\ 1 & \text{if } \varphi = \psi \end{cases}$$

$\varphi, \psi \in S$

Orthonormal Basis

A basis for \mathbb{R}^k which is an o.n.-set is called an o.n.b

$$B = \{\varphi_j\}_{j=1}^k \text{ o.n.b}$$

$$x \in \mathbb{R}^k \implies x = \sum_{j=1}^k (x, \varphi_j) \varphi_j \quad (x, \varphi_j) = \varphi_j^T x$$

$$\implies \|x\|^2 = \sum_{j=1}^k (x, \varphi_j)^2$$

Also if $x, y \in \mathbb{R}^k$ then

$$(x, y) = \sum_{j=1}^k (x, e_j)(y, e_j)$$

From observe

any o.n.-set in \mathbb{R}^k is

either a basis for \mathbb{R}^k

OR

it can be extended to an onb for \mathbb{R}^k

W a subspace of \mathbb{R}^k

Orthogonal complement of W is defined as

$$W^\perp = \{x \in \mathbb{R}^k : (x, w) = 0 \forall w \in W\}$$

We observed the following facts.

1 W^\perp is a subspace of \mathbb{R}^k

2 If B_W is a basis for W and
 B_{W^\perp} is a basis for W^\perp

then

$B = B_W \cup B_{W^\perp}$
is a basis for \mathbb{R}^k

3 $\dim W + \dim W^\perp = \dim \mathbb{R}^k = k$

4. \mathcal{O}_W an o.n.-b. for W and
 \mathcal{O}_{W^\perp} " " " W^\perp then

$\mathcal{O} = \mathcal{O}_W \cup \mathcal{O}_{W^\perp}$ is an o.n.-b. for \mathbb{R}^k

5 Any vector $x \in \mathbb{R}^k$ can be decomposed as a sum

$x = x_W + x_{W^\perp}$ where
 $x_W \in W$ and $x_{W^\perp} \in W^\perp$ in
a unique manner

6. Pythagoras Theorem:

$$\|x\|^2 = \|x_W\|^2 + \|x_{W^\perp}\|^2$$

7 x_W : Orthogonal projection
of x onto W

x_{W^\perp} : orthogonal projection
of x onto W^\perp

Example: \mathbb{R}^3

$$W = \left\{ x = \begin{pmatrix} a \\ a \\ a \end{pmatrix} : a \in \mathbb{R} \right\}$$

W is a subspace

$\beta_W = u_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ is a basis for W

$\dim W = 1$

What is W^\perp ?

$$W^\perp = \left\{ x = \begin{pmatrix} \alpha \\ \beta \\ -\alpha - \beta \end{pmatrix} : \alpha, \beta \in \mathbb{R} \right\}$$

$\beta_{W^\perp} : w_1 = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} ; w_2 = \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix}$ is a basis for W^\perp

We see that

$$\dim W^\perp = 2$$

$$\dim W + \dim W^\perp = 1 + 2 = \dim \mathbb{R}^3$$

If we set

$$\mathcal{B}_0 = \mathcal{B}_W \cup \mathcal{B}_{W^\perp}$$

$$= u_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, w_1 = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}, w_2 = \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix}$$

These are l.i. (Easy to check)

They form a basis for \mathbb{R}^3 since any three

l.i. vectors in \mathbb{R}^3 form a basis for \mathbb{R}^3

$B_W: u_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ basis for W

$$O_W = \varphi_1 = \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \leftarrow$$

$B_{W^\perp}: w_1 = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}, w_2 = \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix}$ to

Apply G-S orthonormalization B_{W^\perp}

$$v_1 = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}$$

$$\|v_1\|^2 = 2$$

$$\psi_1 = \frac{v_1}{\|v_1\|} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}$$

$$v_2 = \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix} - \frac{(v_2, v_1)}{\|v_1\|^2} v_1$$

$$= \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix} - \frac{1}{2} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}$$

$$= \begin{pmatrix} -1/2 \\ -1/2 \\ -1/2 \end{pmatrix}$$

$$\|v_2\|^2 = \frac{1}{2^2} (1+2+1)$$

$$\frac{v_2}{\|v_2\|} = \psi_2 = \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ 2 \\ -1 \end{pmatrix}$$

$$\mathcal{G}_{W^\perp} \cdot \psi_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \quad \psi_2 = \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ 2 \\ -1 \end{pmatrix} \leftarrow$$

$$\mathcal{G} = \mathcal{G}_W \cup \mathcal{G}_{W^\perp} \left. \begin{array}{l} \\ \\ \\ \end{array} \right\} \\ = \psi_1, \psi_2, \psi_2$$

is an o.n.b. for \mathbb{R}^3

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

Expand in terms
of the o.n.b for \mathbb{R}^3

The expansion is

$$\underline{x} = \underbrace{(x, \varphi_1)}_{\checkmark} \varphi_1 + \underbrace{(x, \psi_1)}_{\checkmark} \psi_1 + \underbrace{(x, \psi_2)}_{\checkmark} \psi_2 \dots \text{(I)}$$

$$(x, \varphi_1) = \frac{x_1 + x_2 + x_3}{\sqrt{3}}, \quad (x, \psi_1) = \frac{x_1 - x_3}{\sqrt{2}}$$

$$(x, \psi_2) = \frac{-x_1 + 2x_2 - x_3}{\sqrt{6}}$$

$$\text{LHS (I)} =$$

$$\left\{ \frac{x_1 + x_2 + x_3}{\sqrt{3}} \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\} \leftarrow$$

$$\left\{ + \frac{x_1 - x_3}{\sqrt{2}} \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} \right\} \leftarrow$$

$$\left\{ + \frac{-x_1 + 2x_2 - x_3}{\sqrt{6}} \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ 2 \\ -1 \end{pmatrix} \right\} \leftarrow$$

$$= \underbrace{\begin{pmatrix} (x_1 + x_2 + x_3)/3 \\ (x_1 + x_2 + x_3)/3 \\ (x_1 + x_2 + x_3)/3 \end{pmatrix}}_{x_W} + \underbrace{\begin{pmatrix} (2x_1 - x_2 - x_3)/3 \\ (-x_1 + 2x_2 - x_3)/3 \\ (-x_1 - x_2 + 2x_3)/3 \end{pmatrix}}_{x_{W^\perp}}$$

$$= x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

For example if

$$x = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} \in \mathbb{R}^3$$

$$x_W = \begin{pmatrix} 2 \\ 2 \\ 2 \end{pmatrix}$$

⏟
 $\in W$

$$x_{W^\perp} = \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix}$$

⏟
 $\in W^\perp$

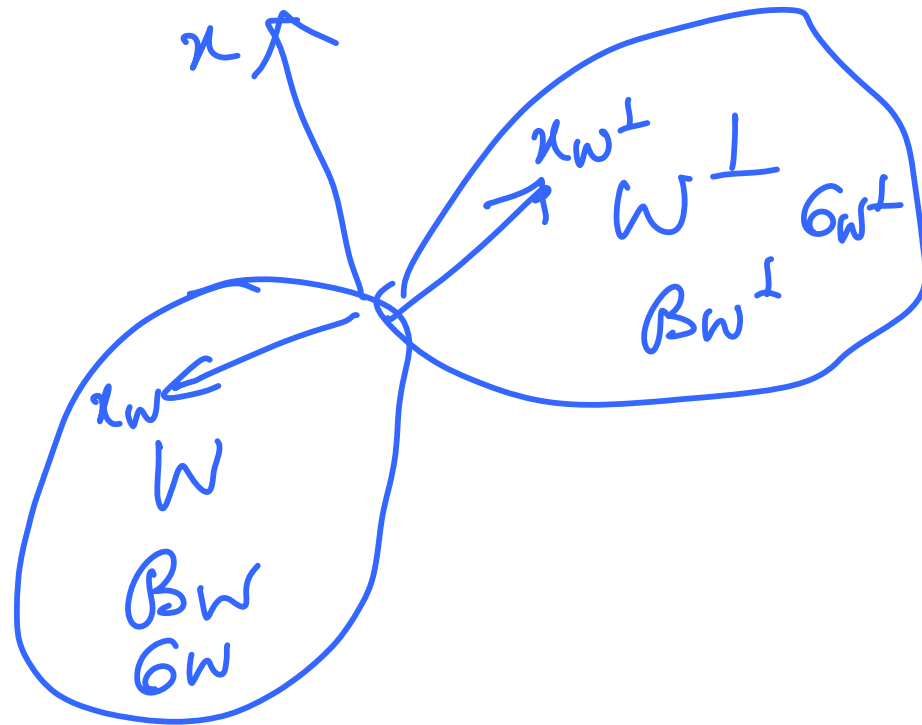
$$x = x_W + x_{W^\perp}$$

Pythagoras: $\|x\|^2 = 1^2 + 2^2 + 3^2 = 1 + 4 + 9 = 14$

$$\|x_w\|^2 = 2^2 + 2^2 + 2^2 = 4 + 4 + 4 = 12$$

$$\|x_{w^\perp}\|^2 = (-1)^2 + 0^2 + 1^2 = 1 + 1 = 2$$

$$\|x_w\|^2 + \|x_{w^\perp}\|^2 = 12 + 2 = 14 \\ = \|x\|^2$$



One More Simple Property of Orth Comp

\mathbb{R}^k , W a subspace of \mathbb{R}^k
 $\dim W = d$

W^\perp : orth compl of W
 $\dim W^\perp = k - d$

$$X = W^\perp$$

X is a subspace
 $\dim X = k - d$

$$X^\perp \text{ orth. comp. of } X \\ = \left\{ x \in \mathbb{R}^k : (x, y) = 0 \forall y \in X = W^\perp \right\}$$

Clearly $x \in W \implies x \in X^\perp$

$$\boxed{W \subseteq X^\perp}$$

$$\leftarrow \frac{W \subseteq (W^\perp)^\perp}{\underline{\underline{\hspace{1cm}}}}$$

$$\dim X + \dim X^\perp = \dim \mathbb{R}^k$$

$$\dim W^\perp + \dim (W^\perp)^\perp = \dim \mathbb{R}^k$$

Also have

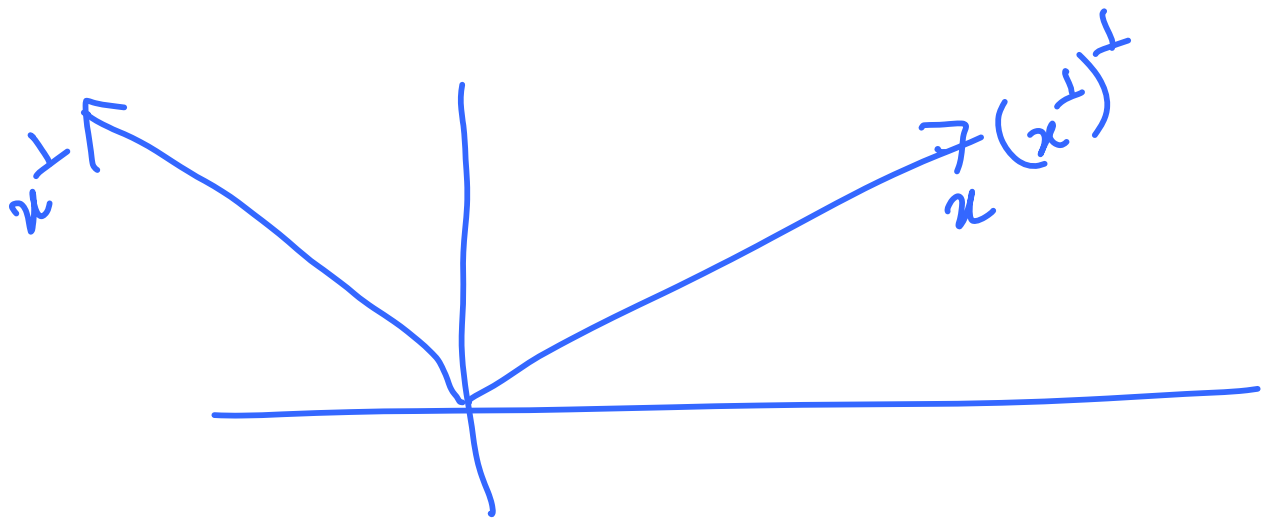
$$\dim W^\perp + \dim W = \dim \mathbb{R}^k$$

\implies

$$\boxed{\dim W = (\dim W^\perp)^\perp}$$

\implies

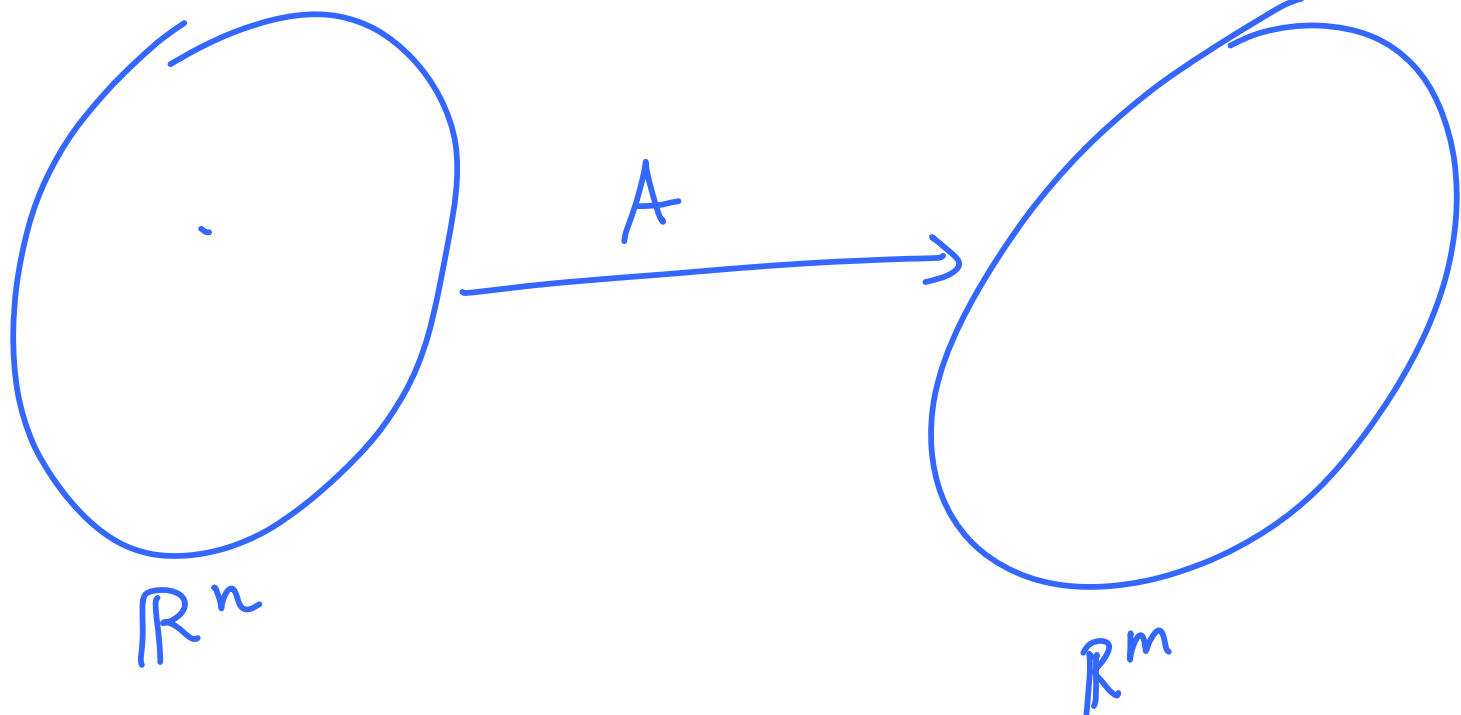
$$W = (W^\perp)^\perp$$



Context of Matrices

$$A \in \mathbb{R}^{m \times n}$$

The Four Fundamental Bases



↓
Two Subspaces
 R_{A^T} and N_A

$$N_A = \{x \in \mathbb{R}^n : Ax = 0_m\}$$

Two Subspaces
 R_A and N_{A^T}

$$N_{A^T} = \{x \in \mathbb{R}^m : A^T x = 0_n\}$$

$$\mathcal{R}_{A^T} = \{x \in \mathbb{R}^n : x = A^T b \text{ for } b \in \mathbb{R}^m\}$$

$$\mathcal{R}_A = \{b \in \mathbb{R}^m : b = Ax \text{ for } x \in \mathbb{R}^n\}$$

Look at N_A, \mathcal{R}_{A^T}

$$x \in N_A \iff Ax = 0_m$$

$$\iff (Ax, b) = 0 \quad \forall b \in \mathbb{R}^m$$

$$\iff b^T (Ax) = 0 \quad \forall b \in \mathbb{R}^m$$

$$\iff (b^T A)x = 0 \quad \forall b \in \mathbb{R}^m$$

$$\Leftrightarrow (A^T b)^T x = 0 \quad \forall b \in \mathbb{R}^m$$

$$\Leftrightarrow (x, A^T b) = 0 \quad \forall b \in \mathbb{R}^m$$

$\Leftrightarrow x$ orth to all vectors
of the form $A^T b$, $b \in \mathbb{R}^m$

$\Leftrightarrow x$ is orth to all vect in

\mathcal{R}_{A^T}

$$\Leftrightarrow x \in \mathcal{R}_{A^T}^\perp$$

$\mathcal{N}_A = \mathcal{R}_{A^T}^\perp$	$\mathcal{N}_{A^T} = \mathcal{R}_A^\perp$
$\mathcal{N}_A^\perp = \mathcal{R}_{A^T}$	$\mathcal{N}_{A^T}^\perp = \mathcal{R}_A$
\mathbb{R}^n	\mathbb{R}^m

$$\dim R_{A^T} + \dim R_{A^T}^\perp = n$$

$$\rightarrow \rho_{A^T} + \nu_A = n$$

On the other hand Rank-Nullity Thm

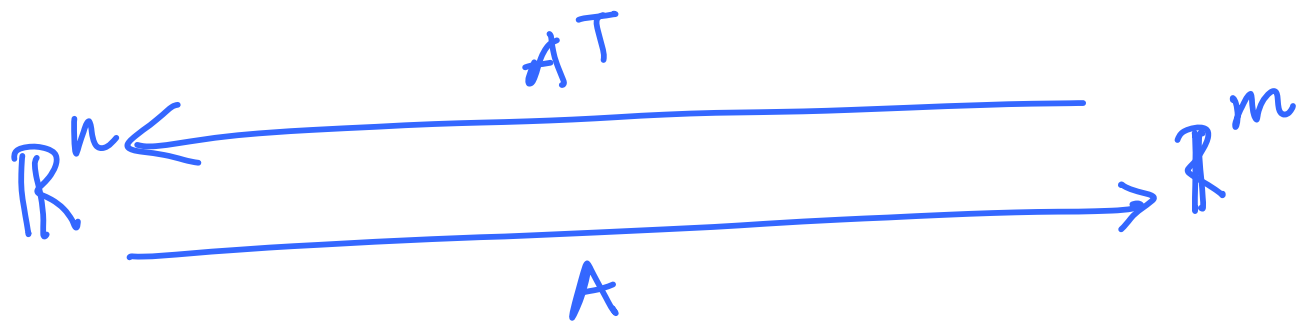
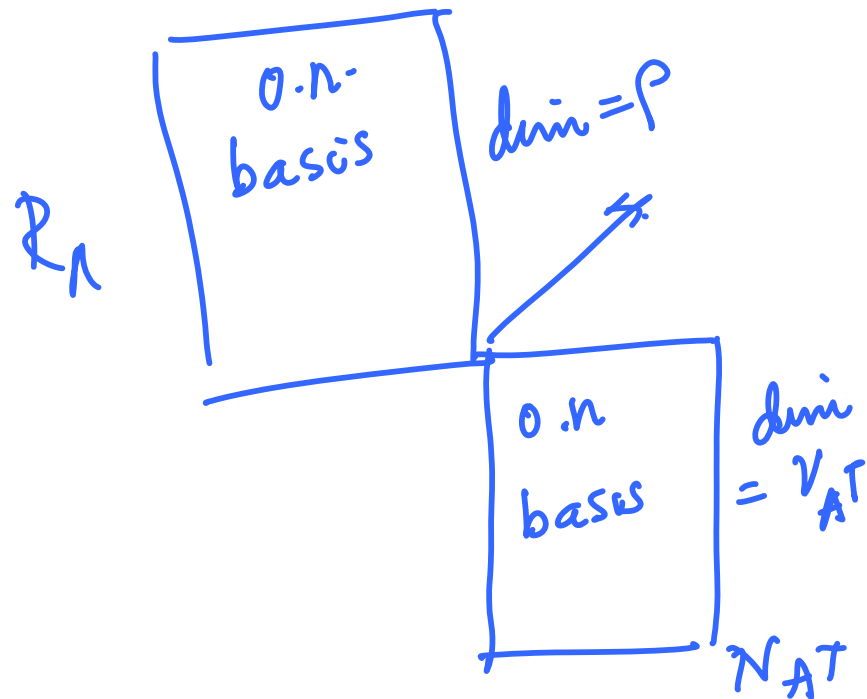
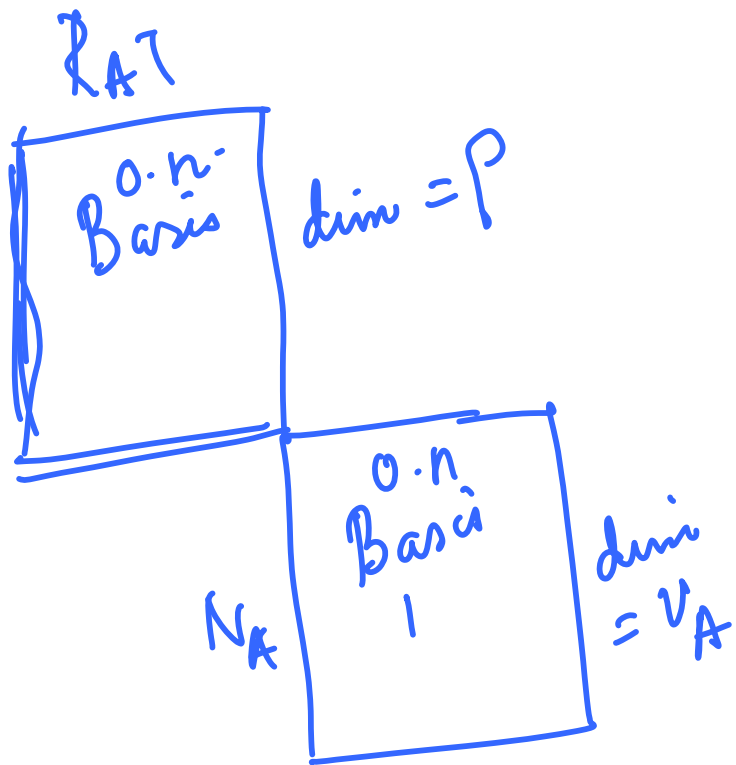
gives

$$\rho_A + \nu_A = n$$

\Rightarrow

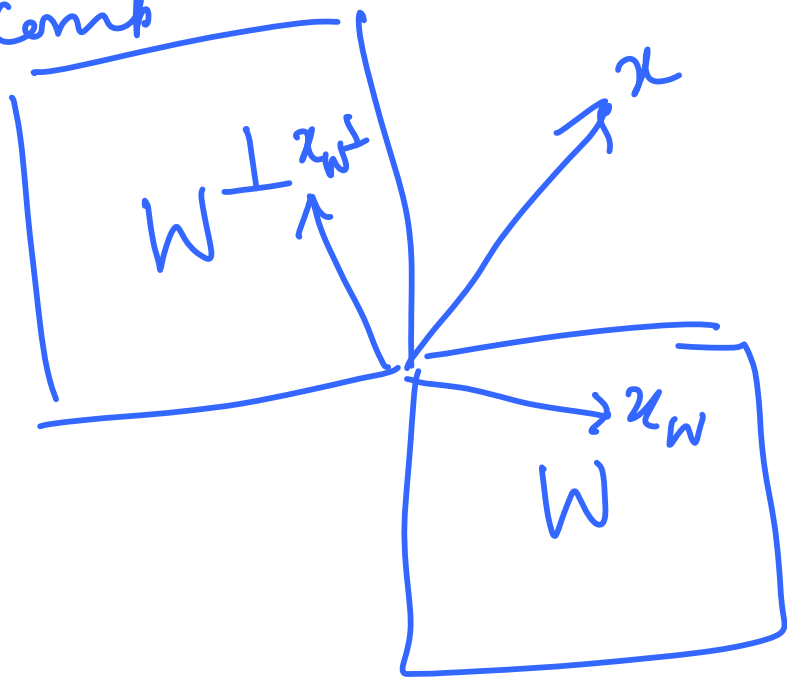
$$\rho_A = \rho_{A^T}$$

|| For any matrix (over reals)
its rank = rank of its transpose



W subspace of \mathbb{R}^k

W^\perp ortho comp



$$x \in \mathbb{R}^k$$

\Rightarrow

$$x = x_W + x_{W^\perp}$$

\mathbb{R}^k

Given x find a vector $w_0 \in W$ s.t

$$\|x - w_0\|^2 < \|x - w\|^2 \quad \forall w \neq w_0, w \in W$$

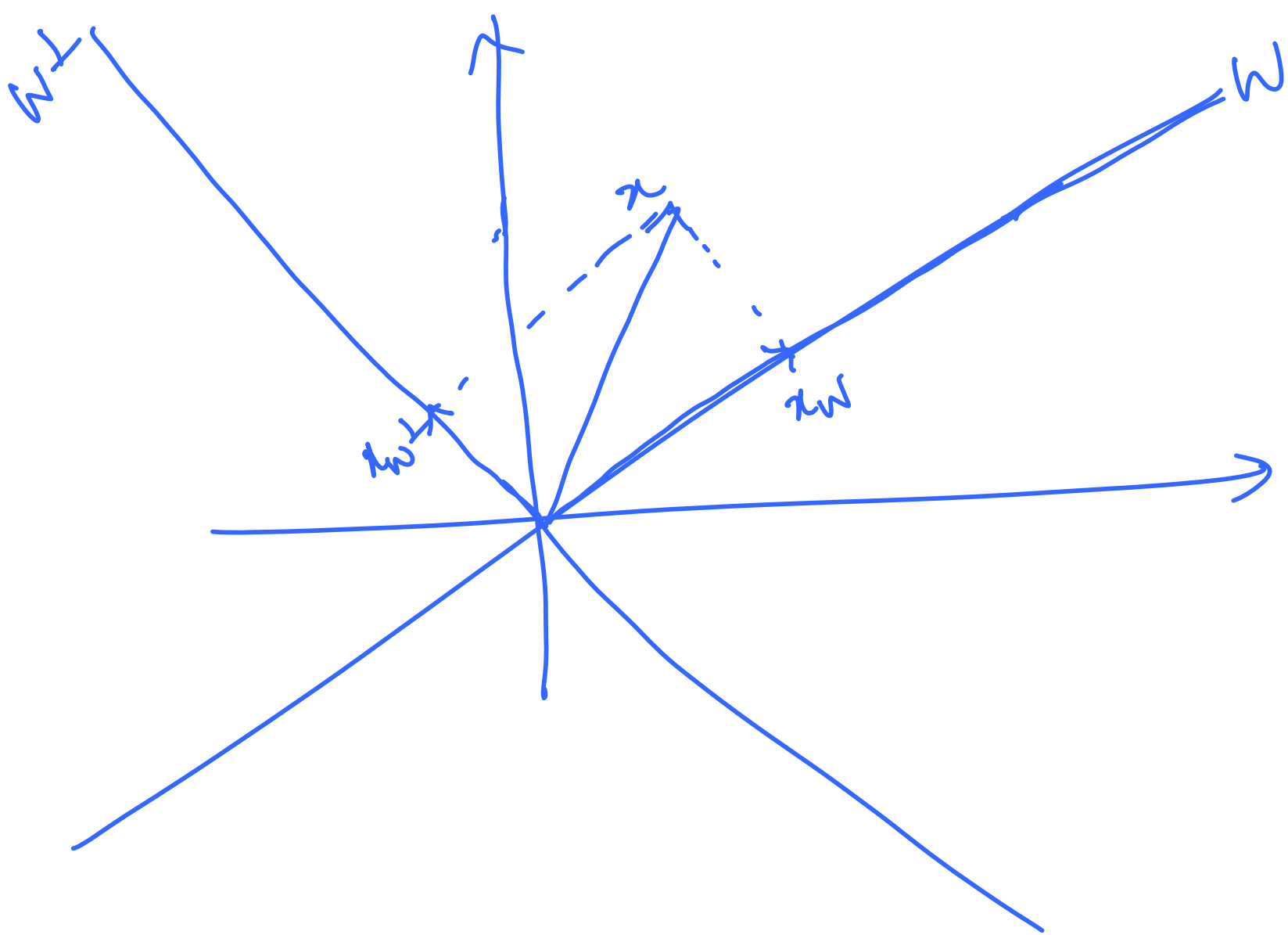
Best Approximation Problem

\mathbb{R}^k , W subspace of \mathbb{R}^k

Given $x \in \mathbb{R}^k$ find $w_0 \in W$

s.t. $\|x - w_0\|^2 < \|x - w\|^2 \quad \forall w \in W, w \neq w_0$

The vector w_0 which gives this least error for x is precisely x_W — the orthogonal proj of x onto W



x_W . The orth proj of x onto W gives the best app. of x from W .