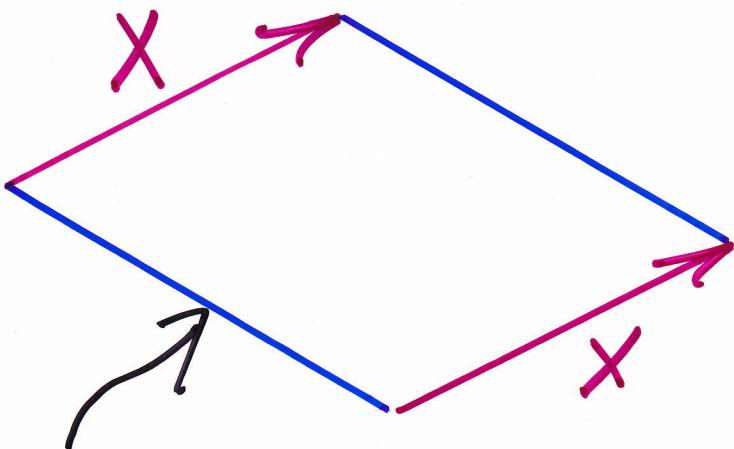


VECTOR REPRESENTATION

PARALLEL ARROWS WITH
SAME LENGTH AND SAME
DIRECTION PICTURE THE
SAME VECTOR.

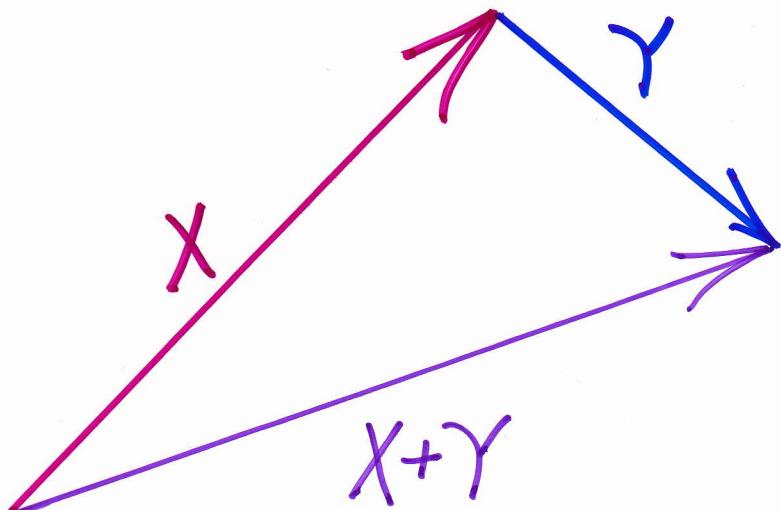


PARALLELOGRAM
IN SPACE

$$\|X\| = \text{LENGTH OF } X$$

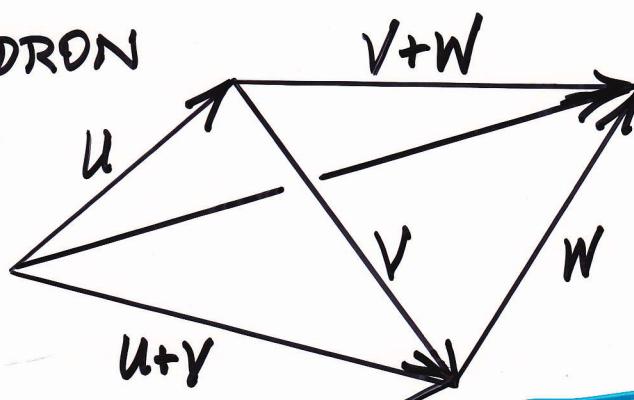
VECTOR ADDITION

HEAD TO TAIL



ASSOCIATIVE
LAW

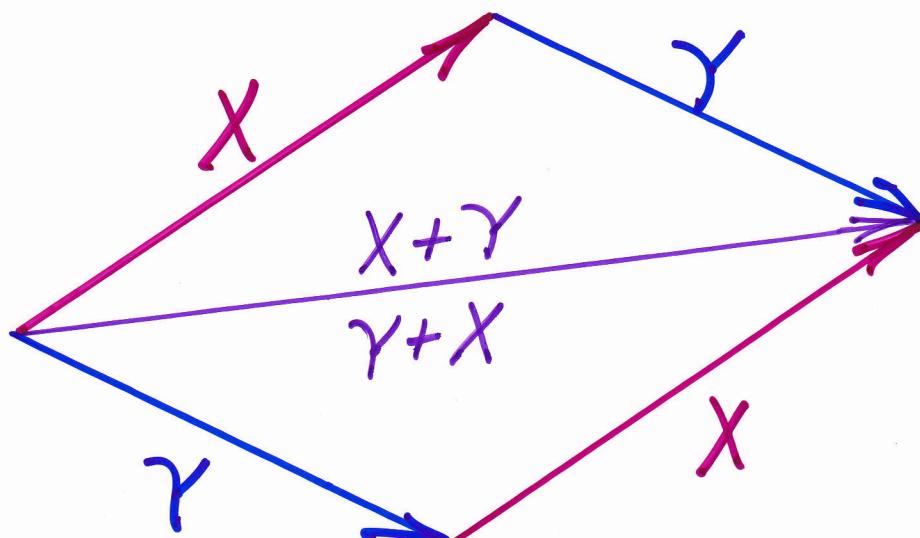
TETRAHEDRON
IN
SPACE



$$(u+v)+w = u+(v+w)$$

VECTOR ADDITION

PARALLELOGRAM & COMMUTATIVE LAWS

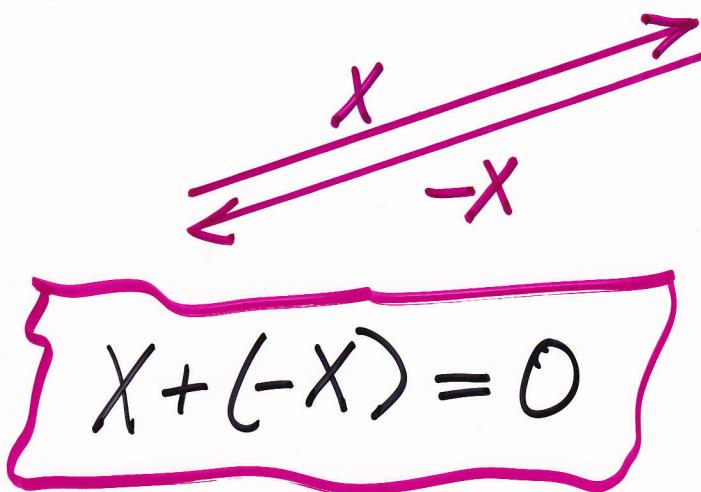


$$X+Y = Y+X$$

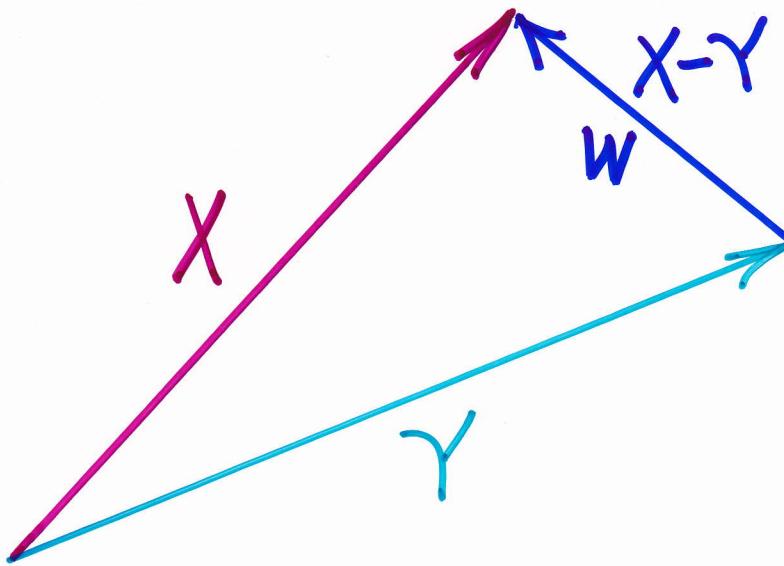
ZERO VECTOR

ANY POINT IN SPACE IS A PICTURE OF THE ZERO VECTOR, $\vec{0}$. THE ZERO VECTOR HAS ZERO LENGTH AND NO DIRECTION (OR ALL DIRECTIONS SIMULTANEOUSLY).

NEGATIVE OF VECTOR
TO NEGATE A VECTOR REVERSE ITS DIRECTION.



VECTOR SUBTRACTION



FROM HEAD TO TAIL ADDITION

$$X = Y + W$$

∴ $W = X - Y$

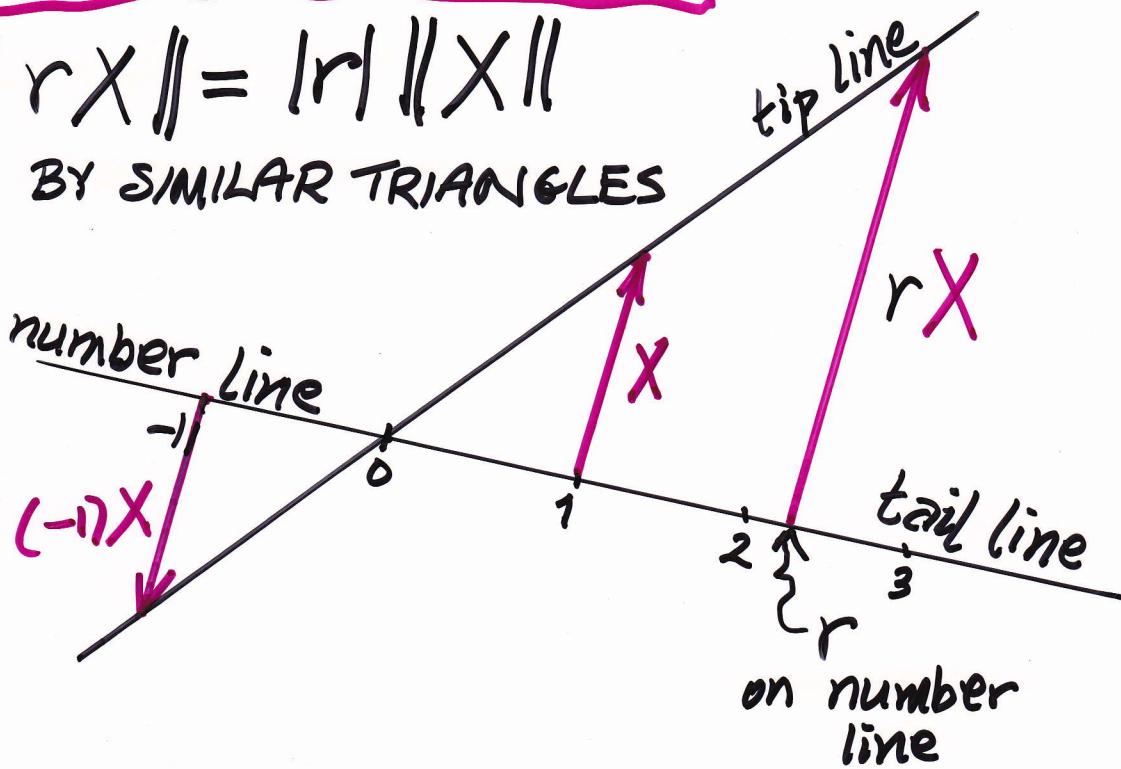
MULTIPLY A VECTOR BY A NUMBER

$$\|X\| = \text{LENGTH of } X$$

$$|r| = \sqrt{r^2}$$

$$\|rX\| = |r| \|X\|$$

BY SIMILAR TRIANGLES

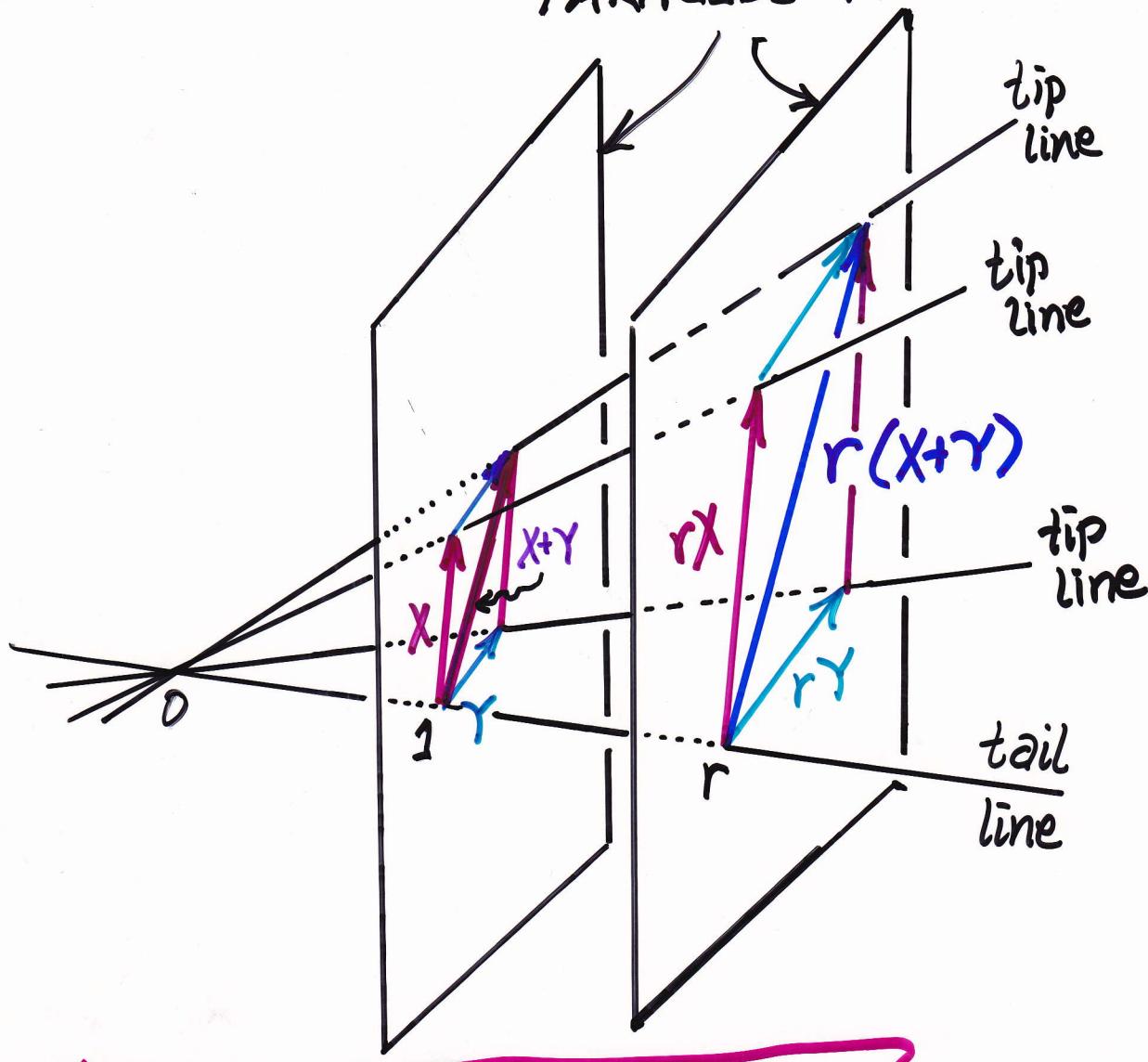


NOTICE MULTIPLYING X BY A
NEGATIVE NUMBER REVERSES
ITS DIRECTION, $(-1)X = -X$

$$\text{SO } \therefore (-1)^2 = 1.$$

DISTRIBUTIVE LAW FOR MULTIPLICATION of a VECTOR BY ANY REAL NUMBER

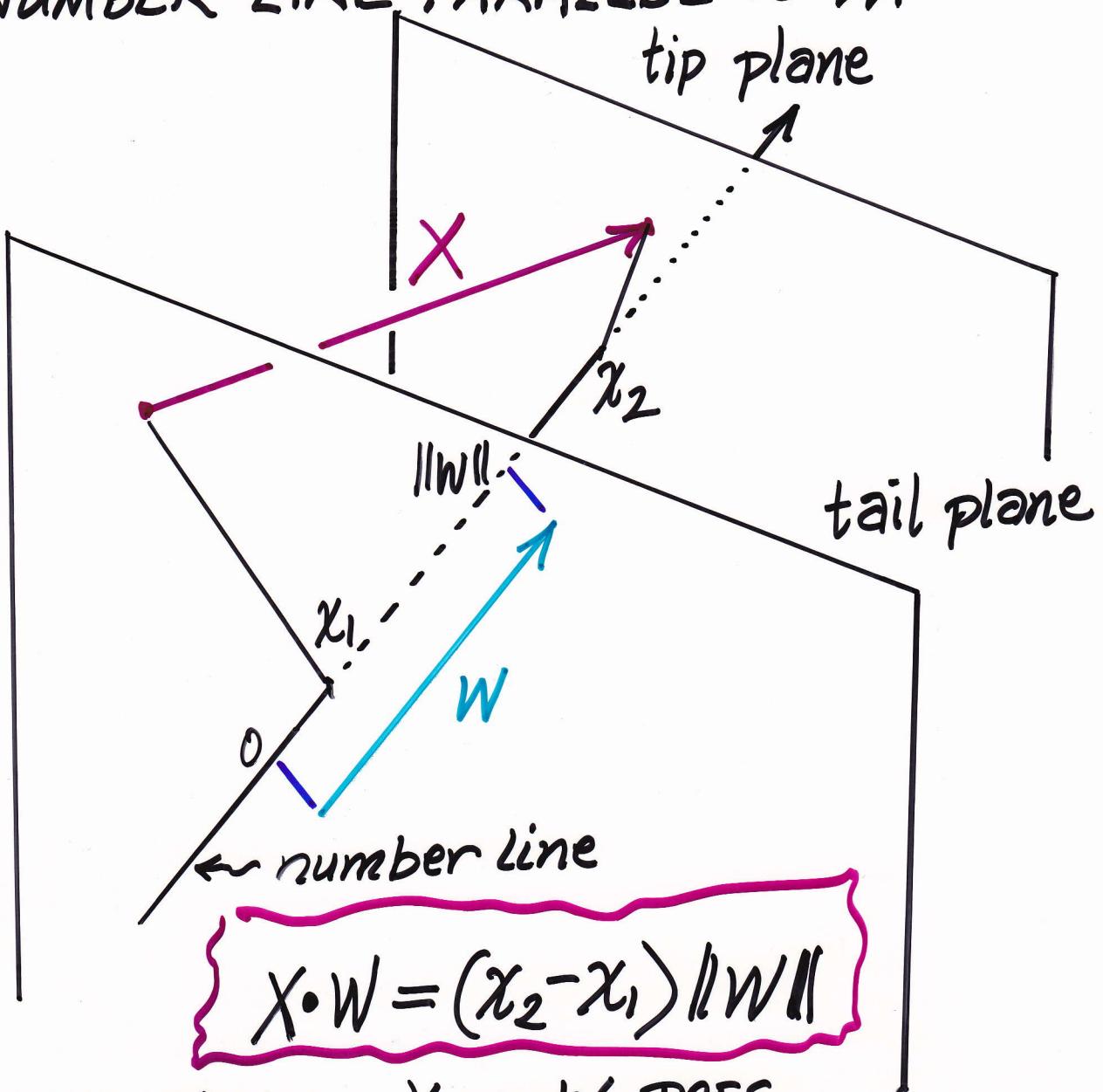
PARALLEL PLANES



$$r(X+Y) = rX + rY$$

DOT PRODUCT of TWO VECTORS IS A REAL NUMBER

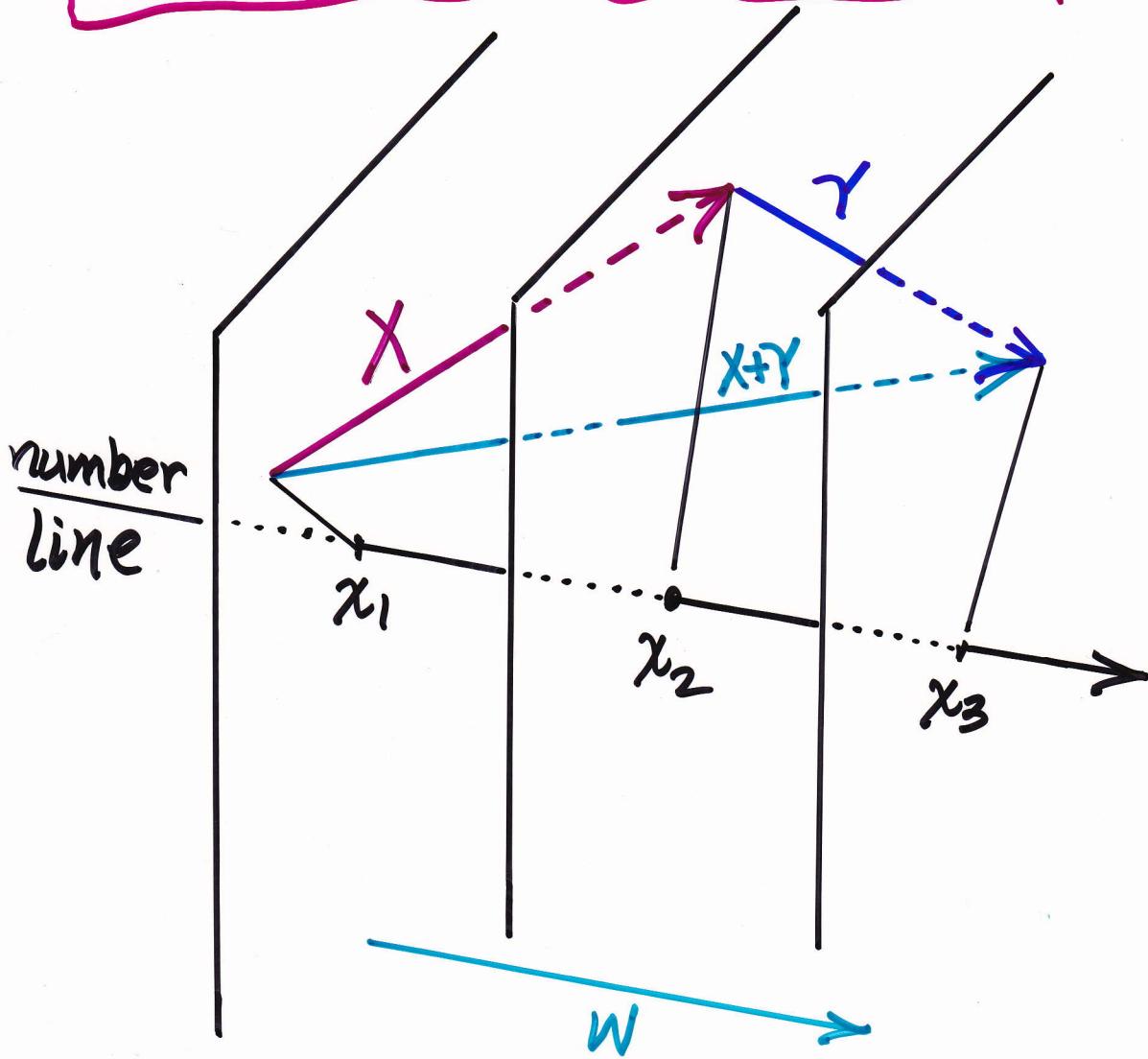
TWO PLANES PERPENDICULAR TO
NUMBER LINE PARALLEL TO w .



NOTE MOVING X OR w DOES
NOT CHANGE $x_2 - x_1$.

DISTRIBUTIVE LAW FOR DOT PRODUCT OF VECTORS

$$(X+Y) \cdot W = X \cdot W + Y \cdot W$$



$$X \cdot W = (x_2 - x_1) \|W\|$$

$$Y \cdot W = (x_3 - x_2) \|W\|$$

$$X \cdot W + Y \cdot W = (x_3 - x_1) \|W\| = (X+Y) \cdot W$$

COMMUTATIVE LAW FOR DOT PRODUCT

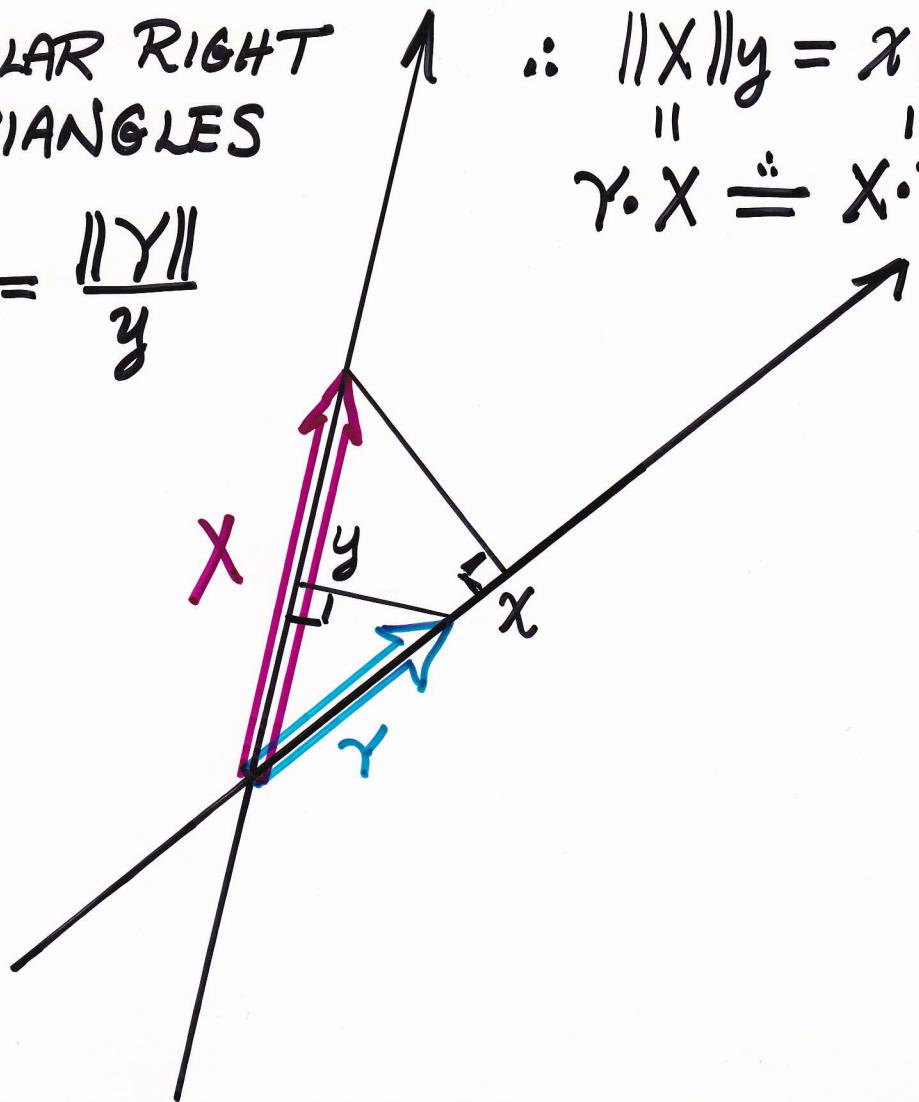
$$X \cdot Y = Y \cdot X$$

PUT TAILS TOGETHER
THEN X & Y DETERMINE A PLANE

SIMILAR RIGHT
TRIANGLES

$$\frac{\|X\|}{x} = \frac{\|Y\|}{y}$$

$$\therefore \|X\|y = \|Y\|x \\ Y \cdot X \doteq X \cdot Y$$



DOT PRODUCT EXAMPLES

If X and Y point in the same direction then $X \cdot Y = \|X\| \|Y\|$, so just multiply lengths.

$X \cdot Y = 0$ if and only if
 X & Y are PERPENDICULAR

From the picture defining the dot product we see

$$(-X) \cdot Y = - (X \cdot Y)$$

so by the commutative law

$$(-X) \cdot Y = - (X \cdot Y) = X \cdot (-Y)$$

and from the formula defining the dot product then

$$(rX) \cdot Y = X \cdot (rY) = r(X \cdot Y)$$

for any real number r .

MORE DOT PRODUCT EXAMPLES

$$X \cdot X = \|X\|^2, \quad \|X\| = \sqrt{X \cdot X}$$

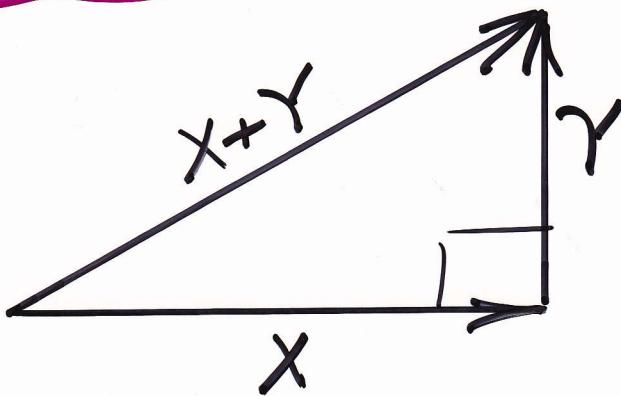
$$\|X+Y\|^2 = \underbrace{(X+Y) \cdot (X+Y)}$$

$$= X \cdot X + Y \cdot Y + X \cdot Y + Y \cdot X$$

$$= \|X\|^2 + \|Y\|^2 + 2(X \cdot Y)$$

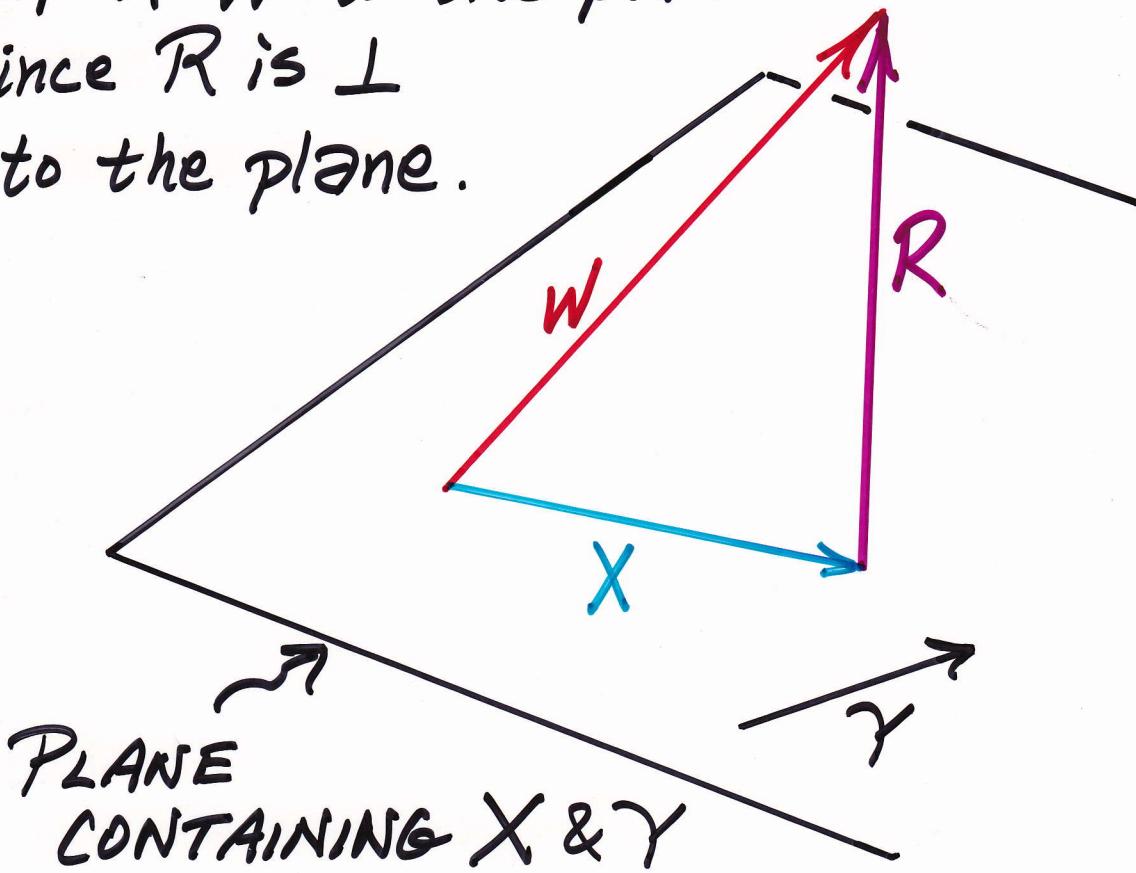
$$\boxed{X \perp Y \Rightarrow \|X+Y\|^2 = \|X\|^2 + \|Y\|^2}$$

(PYTHAGOREAN THEOREM)



STILL MORE DOT PRODUCT EXAMPLES

NOTICE $\|R\|$ is the distance from tip of W to the plane since R is \perp to the plane.



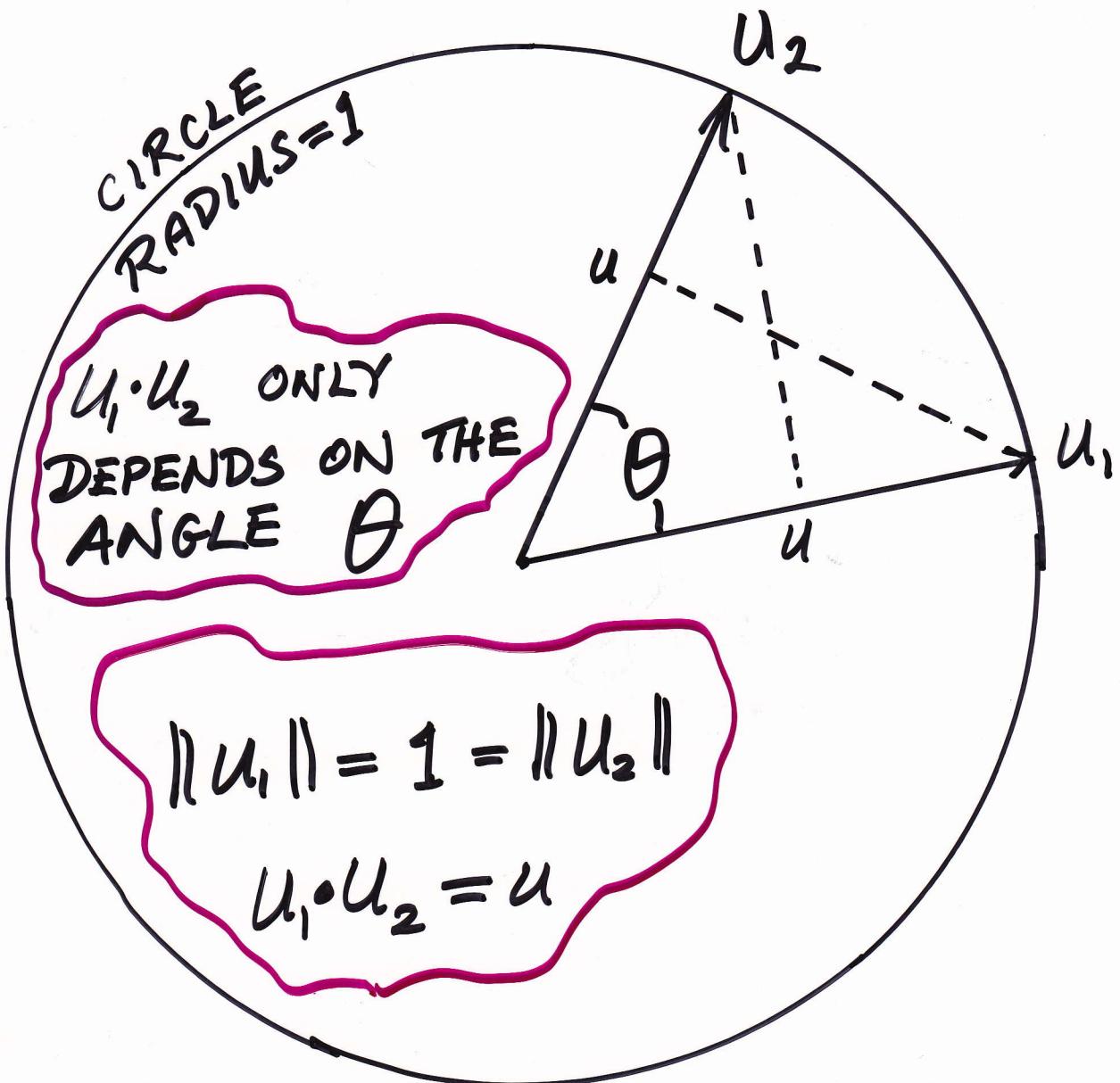
$R \perp$ TO PLANE CONTAINING X & Y

$$X \cdot R = 0 = Y \cdot R$$

$$W \cdot Y = (X + R) \cdot Y = X \cdot Y$$

ALSO $\boxed{\|R\|^2 = \|W\|^2 - \|X\|^2}$

UNIT VECTORS & DOT PRODUCTS



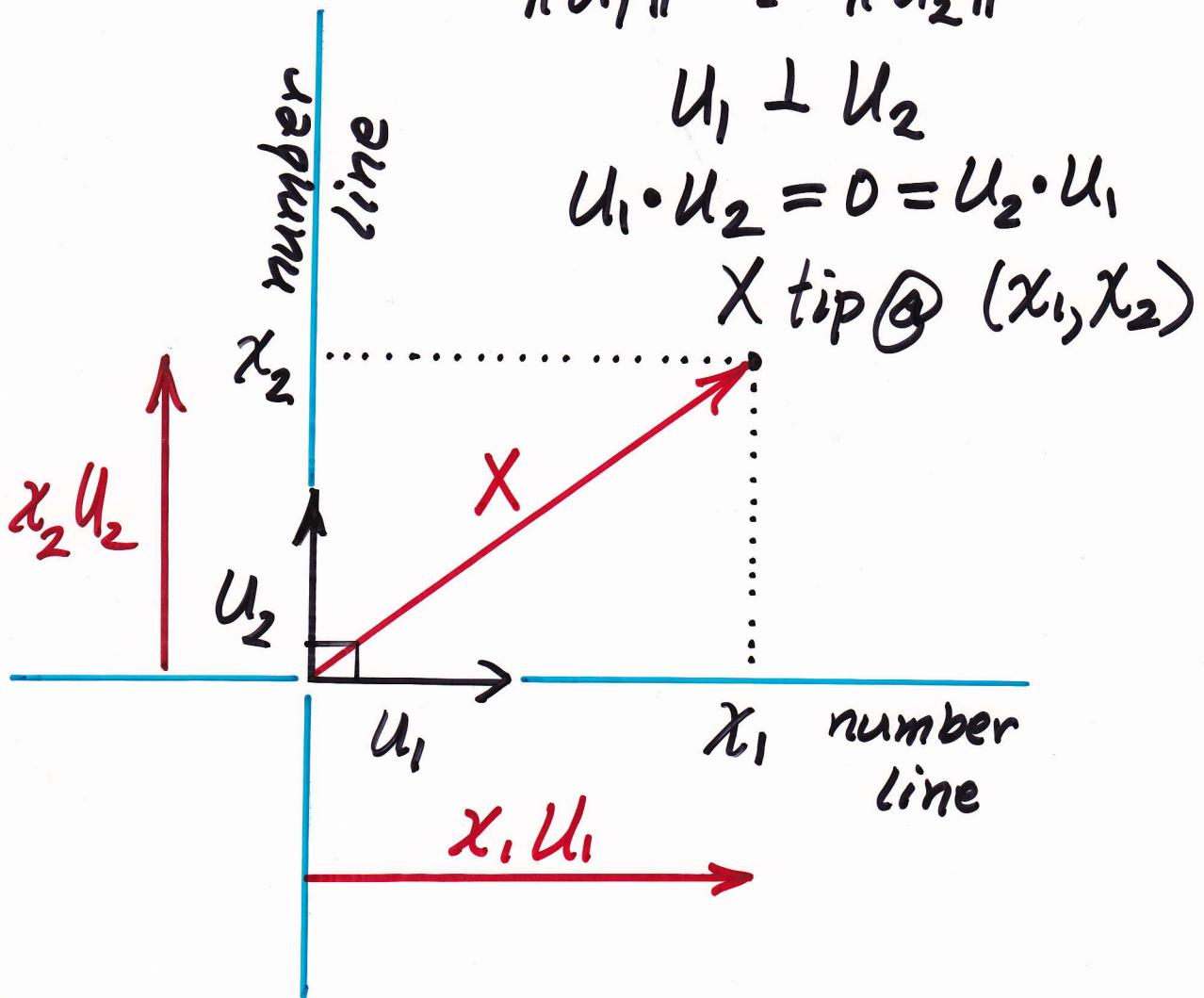
$u = 1$ if and only if $u_1 = u_2$

$u = 0$ if and only if $u_1 \perp u_2$

$|u| \leq 1$ and $u = -1$ means $u_1 = -u_2$.

PERPENDICULAR UNIT VECTORS IN PLANE

$$\|u_1\| = 1 = \|u_2\|$$



$$X = x_1 u_1 + x_2 u_2$$

$$X \cdot u_1 = x_1 u_1 \cdot u_1 = x_1$$

$$X \cdot u_2 = x_2 u_2 \cdot u_2 = x_2$$

$$X = (X \cdot u_1)u_1 + (X \cdot u_2)u_2$$

UNKNOWN & RANDOM VARIABLES

PICTURED AS VECTORS

ADDITION of UNKNOWN IS
ADDITION of VECTORS

MULTIPLICATION BY REAL NUMBER
IS THE SAME FOR UNKNOWN
AND VECTORS

DOT PRODUCT of UNKNOWN

$$X \cdot Y = E(XY) \text{ so } \|X\|^2 = E(X^2)$$

IS COMPUTED WITH EXPECTATION

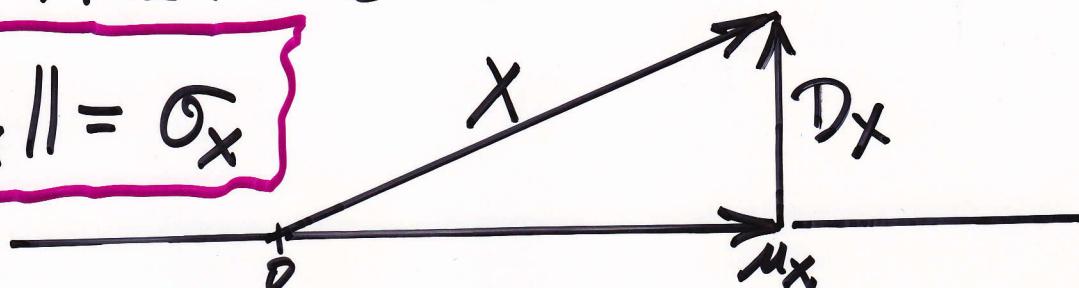
$$X \cdot 1 = E(X1) = E(X) = \mu_X$$

$$D_X = X - \mu_X = \text{DEVIATION}$$

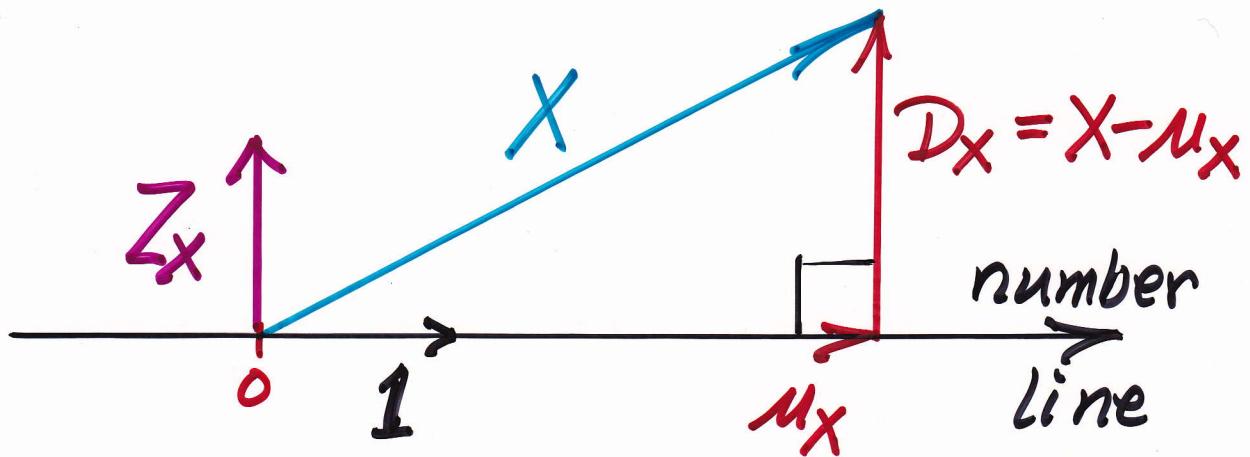
$$r \cdot D_X = E(rD_X) = r E(D_X) = 0$$

\therefore ALL NUMBERS \perp DEVIATIONS

$$\|D_X\| = \sigma_X$$



PICTURE ONE UNKNOWN
OR
RANDOM VARIABLE
A RIGHT TRIANGLE



$$Z_X = \frac{D_X}{\sigma_X} = \frac{D_X}{\|D_X\|}$$

$$\|Z_X\| = 1 = \|1\| \text{ & } Z_X \perp 1$$

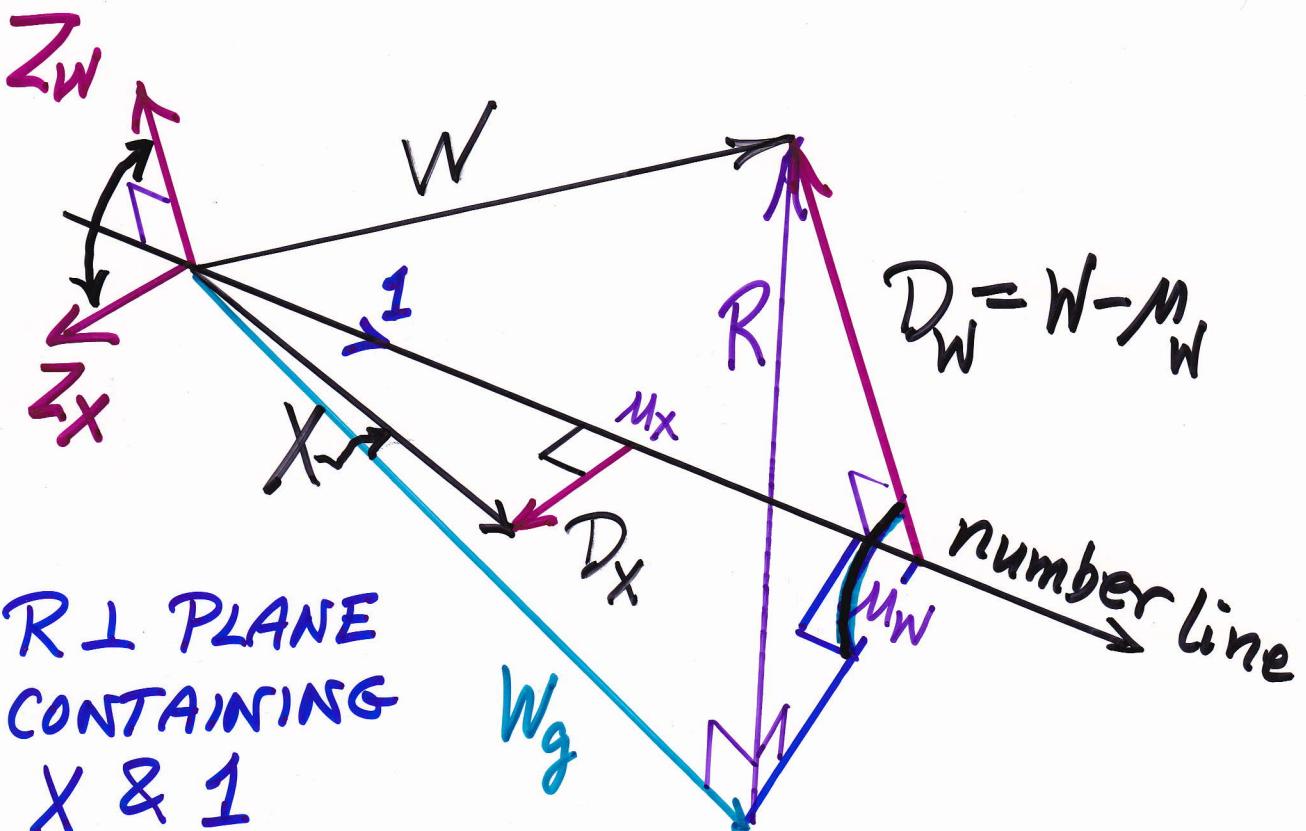
$$X = \mu_X 1 + \sigma_X Z_X$$

$$X \cdot 1 = \mu_X \quad \& \quad X \cdot Z_X = \sigma_X$$

$$E(X^2) = X \cdot X = \|X\|^2 = \mu_X^2 + \sigma_X^2$$

$$\boxed{E(X^2) = \mu_X^2 + \sigma_X^2}$$

PICTURE TWO UNKNOWNS OR RANDOM VARIABLES



$$\therefore R \cdot Z_X = 0, R \cdot I = 0, R \cdot W_g = 0$$

$$W_g \cdot Z_X = W \cdot Z_X \quad \& \quad W_g \cdot I = W \cdot I$$

$$W_g = (W_g \cdot I)I + (W_g \cdot Z_X)Z_X$$

$$\therefore \boxed{W_g = (W \cdot I)I + (W \cdot Z_X)Z_X}$$

$$W \cdot Z_X = D_w \cdot Z_X = \sigma_w (Z_w \cdot Z_X)$$

LINEAR REGRESSION USING PICTURE FOR TWO UNKNOWNNS OR RANDOM VARIABLES

W_g = "BEST" GUESS FOR
VALUE OF W GIVEN
THE VALUE OF X

$E(R^2)$ = ERROR² EXPECTED WHEN
USING W_g .

$$Z_w \cdot Z_x = \rho = \text{CORRELATION COEFFICIENT}$$

$$W \cdot 1 = E(W_1) = E(W) = \mu_W$$

$$W \cdot Z_x = \sigma_W (Z_w \cdot Z_x) = \sigma_W \rho$$

$$W_g = (W \cdot 1) + (W \cdot Z_x) Z_x$$

$$\therefore W_g = \mu_W + \rho \sigma_W Z_x$$

OR $W_g = \mu_W + \frac{\rho \sigma_W}{\sigma_X} (X - \mu_X)$

$$(Z_w)_{\text{guess}} = \rho Z_x$$

EXPECTED ERROR² USING LINEAR REGRESSION

$$W_g = \mu_w 1 + \rho \sigma_w Z_x$$

$$1 \perp Z_x \text{ & } \|1\| = 1 = \|Z_x\|$$

$$\therefore \|W_g\|^2 = \mu_w^2 + \rho^2 \sigma_w^2$$

$$R \perp W_g \text{ & } W = W_g + R$$

$$\therefore \|W\|^2 = \|W_g\|^2 + \|R\|^2.$$

$$\text{ALSO } \|W\|^2 = \mu_w^2 + \sigma_w^2.$$

$$\begin{aligned} \therefore \mu_w^2 + \sigma_w^2 &= \|W\|^2 = \|W_g\|^2 + \|R\|^2 \\ &= \mu_w^2 + \rho^2 \sigma_w^2 + \|R\|^2 \end{aligned}$$

$$\therefore \sigma_w^2 = \rho^2 \sigma_w^2 + \|R\|^2$$

$$\therefore E(R^2) = \|R\|^2 = \sigma_w^2 - \rho^2 \sigma_w^2$$

$$E(R^2) = (1 - \rho^2) \sigma_w^2$$

