

# Scalar Product

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## Definition

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$\|\mathbf{x}\| = (x_1^2 + x_2^2 + x_3^2)^{1/2}$ . In either case this is the length of the arrow that we use to visualize  $\mathbf{x}$ .



A couple of simple properties of scalar products.

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We're actually going to prove this in the case  $\mathbb{R}^2$ . But first recall the linear transformations on  $\mathbb{R}^2$  given by rotations. That is, if  $\gamma$  is any angle let  $R_\gamma \mathbf{x}$  be the arrow  $\mathbf{x}$  rotated counterclockwise by the angle  $\gamma$ .

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Similarly

$$\|R_\gamma \mathbf{x}\| = ((R_\gamma \mathbf{x})^T (R_\gamma \mathbf{x}))^{1/2} = (\mathbf{x}^T \mathbf{x})^{1/2} = \|\mathbf{x}\|$$

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$$\frac{\mathbf{x}^T \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} = \frac{\cos \theta}{1}.$$

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Example: if  $\mathbf{x} = \begin{pmatrix} 3 \\ 4 \end{pmatrix}$  and  $\mathbf{y} = \begin{pmatrix} -1 \\ 1 \end{pmatrix}$  then  $\|\mathbf{x}\| = 5$  and  $\|\mathbf{y}\| = \sqrt{2}$ ,  $\mathbf{x}^T \mathbf{y} = 1$ .



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$$\cos \theta = \begin{pmatrix} 3/5 \\ 4/5 \end{pmatrix}^T \begin{pmatrix} -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix} = \frac{-3}{5\sqrt{2}} + \frac{4}{5\sqrt{2}} = \frac{1}{5\sqrt{2}}$$

## The Cauchy-Schwarz Inequality

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Some properties of orthogonality:

1. If  $\mathbf{x} \perp \mathbf{y}_1, \mathbf{x} \perp \mathbf{y}_2, \dots, \mathbf{x} \perp \mathbf{y}_n$  then  $\mathbf{x}$  is orthogonal to every vector in  $\text{Span}(\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n)$ . Proof:

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Here  $x_1$  is leading,  $x_2$  and  $x_3$  are free. The basic solutions

$$\begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} -3 \\ 0 \\ 1 \end{pmatrix}$$

are orthogonal to  $\mathbf{a}$ , as is every vector in their span.

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system is equivalent to  $A\mathbf{x} = \mathbf{0}$  where  $A = \begin{pmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \end{pmatrix}$ . We solve that by row-reducing  $A$ :

$$\begin{pmatrix} 1 & -1 & 3 \\ -1 & 2 & -1 \end{pmatrix} \xrightarrow{R_2+R_1} \begin{pmatrix} 1 & -1 & 3 \\ 0 & 1 & 2 \end{pmatrix} \xrightarrow{R_1+R_2} \begin{pmatrix} 1 & 0 & 5 \\ 0 & 1 & 2 \end{pmatrix}$$

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This has leading variables  $x_1$  and  $x_2$  with free variable  $x_3$ , also  $x_1 = -5x_3$

and  $x_2 = -2x_3$  and so the vectors  $\begin{pmatrix} -5\alpha \\ -2\alpha \\ \alpha \end{pmatrix}$  are orthogonal to  $\mathbf{a}_1$  and

$\mathbf{a}_2$ , for any choice of  $\alpha$ .

## Orthogonal Projection

If  $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$  then  $\|\mathbf{x}\| = (x_1^2 + x_2^2)^{1/2}$  is the distance from the point  $(0, 0)$  to  $(x_1, x_2)$ .

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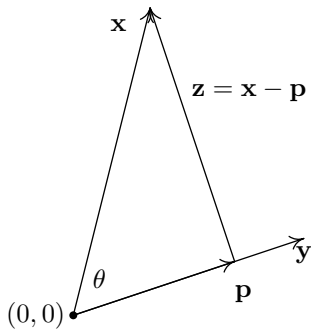
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Suppose we want to find the point on a line that is closest to the point  $(x_1, x_2)$ . Suppose we can express a line as all points that are tips of the vectors  $\alpha\mathbf{y}$  for all  $\alpha \in \mathbb{R}$ .

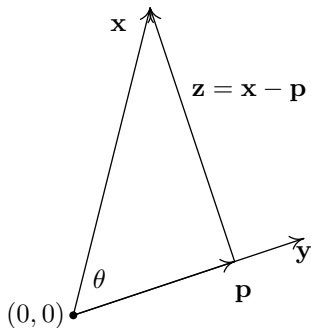


The following is a picture of this setup:



We seek to find the tip of  $\mathbf{p}$ .

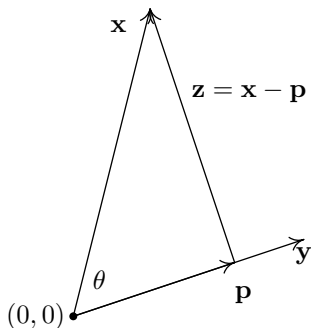
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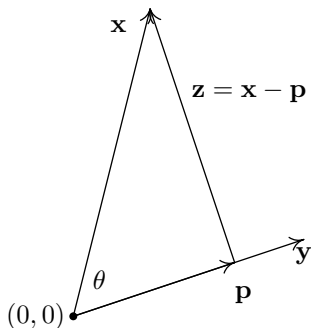


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To get  $\mathbf{p}$  itself we observe that  $\mathbf{u} = (1/\|\mathbf{y}\|)\mathbf{y}$  has the same direction as both  $\mathbf{y}$  and  $\mathbf{p}$ , but has length 1.

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The number  $\alpha = \frac{\mathbf{x}^T \mathbf{y}}{\|\mathbf{y}\|}$  is called the *scalar projection of  $\mathbf{x}$  onto  $\mathbf{y}$* .

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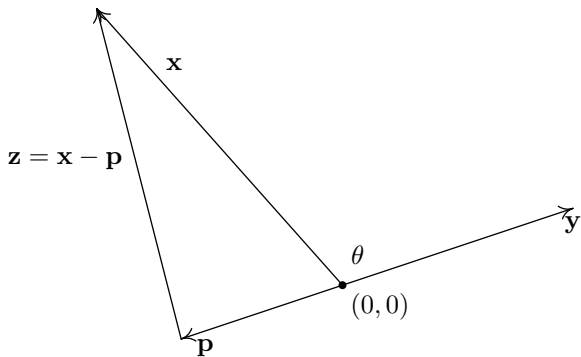
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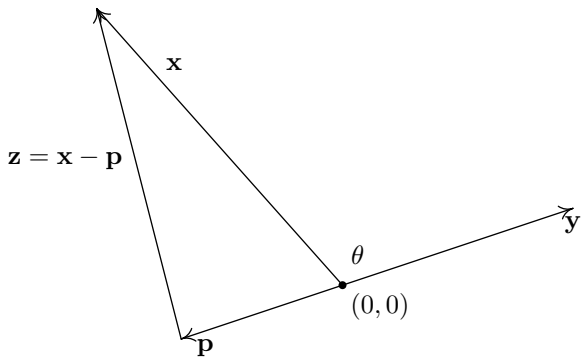
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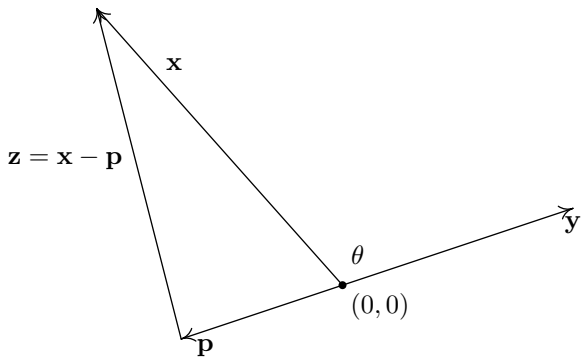


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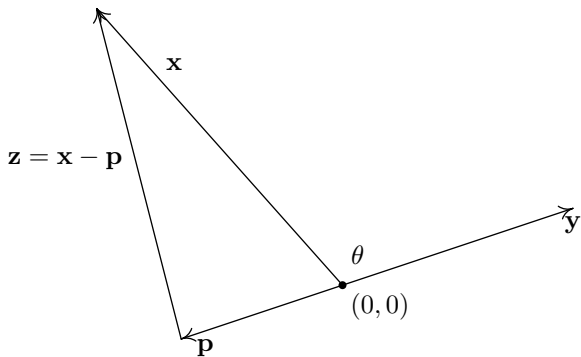
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If we try this with a line  $L$  that does not pass through  $(0,0)$  we simply have to pick two points  $P_0$  and  $P_1$  on the line. The displacement vector from  $P_0$  to  $P_1$  will be denoted  $\overrightarrow{P_0 P_1}$ . All the calculations to get the point on  $L$  closest to a point  $P$  then take place with  $\mathbf{x} = \overrightarrow{P_0 P}$  and  $\mathbf{y} = \overrightarrow{P_0 P_1}$ . When we find  $\mathbf{p}$ , the closest point will be the point  $Q$  such that  $\overrightarrow{P_0 Q} = \mathbf{p}$ .

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To get that closest point, we add the components of  $\mathbf{p}$  to  $P_0$  to get  $Q = (1.8, 1.6)$  and the distance

$$((1 - 1.8)^2 + (4 - 1.6)^2)^{1/2} = \sqrt{6.4} \approx 2.53.$$

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equation of the plane through  $(x_0, y_0, z_0)$  and perpendicular to  $\begin{pmatrix} a \\ b \\ c \end{pmatrix}$  is

$$a(x - x_0) + b(y - y_0) + c(z - z_0) = 0$$