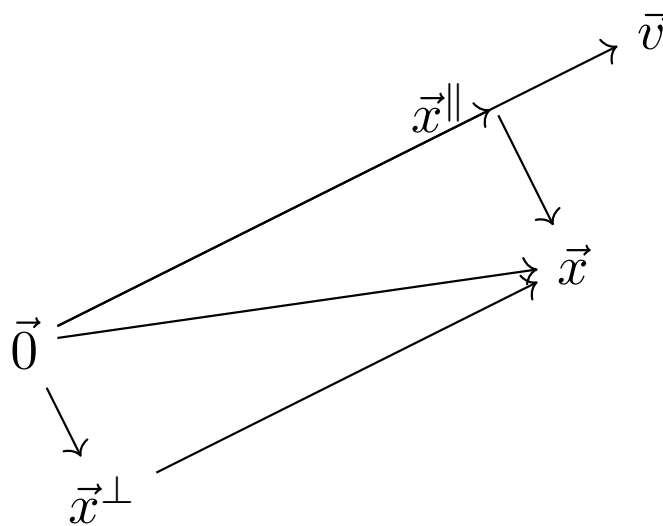


Orthogonal projection

Earlier, we learned about orthogonal projection onto the line spanned by a vector \vec{v} :

Given a nonzero vector \vec{v} in \mathbb{R}^n , we can decompose any vector \vec{x} as $\vec{x}^{\parallel} + \vec{x}^{\perp}$, where \vec{x}^{\parallel} is parallel to \vec{v} and \vec{x}^{\perp} is perpendicular.



We have $x^{\parallel} = \frac{\vec{v} \cdot \vec{x}}{\vec{v} \cdot \vec{v}} \vec{v}$. If \vec{v} has length 1, $\vec{x}^{\parallel} = (\vec{v} \cdot \vec{x}) \vec{v}$.

Now we want to project, not onto a line, but onto a subspace L . Here is the analogous claim:

Given a subspace L in \mathbb{R}^n , we can decompose any vector \vec{x} as $\vec{x}^{\parallel} + \vec{x}^{\perp}$, where \vec{x}^{\parallel} is in L and \vec{x}^{\perp} is in L^{\perp} .

Today, we'll talk about how to compute x^{\parallel} and x^{\perp} , assuming that we have an orthonormal basis $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$ for L . In the next lecture, we'll talk about how to find such an orthonormal basis.

Next week, we will also mention a formula for \vec{x}^{\parallel} directly, without going through the intermediate step of finding an orthonormal basis for L .

Let $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$ be an orthonormal basis for L .

Since \vec{x}^{\parallel} is in L , we can write

$$\vec{x}^{\parallel} = c_1 \vec{v}_1 + \dots + c_k \vec{v}_k$$

for some scalars c_j . We then have

$$\vec{v}_j \cdot \vec{x} = \vec{v}_j \cdot (\vec{x}^{\parallel} + \vec{x}^{\perp}) = \vec{v}_j \cdot \vec{x}^{\parallel} + \vec{v}_j \cdot \vec{x}^{\perp} = \vec{v}_j \cdot \vec{x}^{\parallel} + 0 = \vec{v}_j \cdot \vec{x}^{\parallel}.$$

But we have

$$\vec{v}_j \cdot \vec{x}^{\parallel} = \vec{v}_j \cdot (c_1 \vec{v}_1 + \dots + c_k \vec{v}_k) = c_1 0 + c_2 0 + \dots + c_j 1 + \dots + c_k 0 = c_j.$$

Putting it all together,

$$c_j = \vec{x} \cdot \vec{v}_j.$$

So:

$$\vec{x}^{\parallel} = (\vec{v}_1 \cdot \vec{x}) \vec{v}_1 + \dots + (\vec{v}_k \cdot \vec{x}) \vec{v}_k.$$

$$\vec{x}^{\parallel} = (\vec{v}_1 \cdot \vec{x})\vec{v}_1 + \cdots + (\vec{v}_k \cdot \vec{x})\vec{v}_k.$$

This is the generalization of $\vec{x}^{\parallel} = (\vec{v} \cdot \vec{x})\vec{v}$, when \vec{v} is a unit vector and we are projecting onto the line $\text{Span}(\vec{v})$.

Of course,

$$\vec{x}^{\perp} = \vec{x} - \vec{x}^{\parallel} = \vec{x} - (\vec{v}_1 \cdot \vec{x})\vec{v}_1 - \cdots - (\vec{v}_k \cdot \vec{x})\vec{v}_k.$$

$$\vec{x}^{\parallel} = (\vec{v}_1 \cdot \vec{x})\vec{v}_1 + \cdots + (\vec{v}_k \cdot \vec{x})\vec{v}_k.$$

There is a cute way to write this with matrices. Let

$$Q = \begin{bmatrix} | & | & \cdots & | \\ \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_k \\ | & | & \cdots & | \end{bmatrix}.$$

So $Q^T Q = \text{Id}_k$.

Then

$$x^{\parallel} = Q Q^T \vec{x}.$$

Let's see why:

$$\begin{aligned} Q Q^T \vec{x} &= \begin{bmatrix} | & | & \cdots & | \\ \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_k \\ | & | & \cdots & | \end{bmatrix} \begin{bmatrix} - & \vec{v}_1 & - \\ - & \vec{v}_2 & - \\ & \vdots & \\ - & \vec{v}_k & - \end{bmatrix} \vec{x} = \begin{bmatrix} | & | & \cdots & | \\ \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_k \\ | & | & \cdots & | \end{bmatrix} \begin{bmatrix} \vec{v}_1 \cdot \vec{x} \\ \vec{v}_2 \cdot \vec{x} \\ \cdots \\ \vec{v}_k \cdot \vec{x} \end{bmatrix} \\ &= (\vec{v}_1 \cdot \vec{x})\vec{v}_1 + \cdots + (\vec{v}_k \cdot \vec{x})\vec{v}_k. \end{aligned}$$

So, if Q is an $n \times k$ matrix with $Q^T Q = \text{Id}_k$, then the columns of Q are an orthonormal basis for some k -dimensional subspace L , and $Q Q^T$ is the orthogonal projection onto L .

At this point, I hope you are convinced that orthonormal bases are great. In the next lecture, we'll talk about how to find them.