

Chapter 5 Orthogonality

Recall: Vectors \vec{v}, \vec{w} are said to be orthogonal with respect to an inner product if

$$\langle \vec{v}, \vec{w} \rangle = 0.$$

A basis $\{\vec{v}_1, \dots, \vec{v}_n\}$ of a vector space V is called orthogonal if, $\langle v_i, v_j \rangle = 0$ for all $i \neq j$. The basis is called orthonormal if in addition, each vector has unit length, $\|v_i\| = 1$.

Ex For \mathbb{R}^n

$$\vec{e}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \vec{e}_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \dots, \vec{e}_n = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}.$$

But this is not the only orthonormal basis of \mathbb{R}^n !

Recall: For any non-zero vector v ,

$$\vec{u} = \frac{\vec{v}}{\|\vec{v}\|} \text{ is a unit vector.}$$

Claim: If $\{\vec{v}_1, \dots, \vec{v}_n\}$ is an orthogonal basis of V then $\vec{u}_j = \frac{\vec{v}_j}{\|\vec{v}_j\|}$ $j=1, \dots, n$ forms an orthonormal basis.

$\rightarrow \langle \vec{v}_i, \vec{v}_j \rangle = 0$ for all i, j non-zero

Proposition: If $\vec{v}_1, \dots, \vec{v}_k$ are mutually orthogonal non-zero vectors then they are linearly independent.

Proof: Consider

$$\vec{v} = c_1 \vec{v}_1 + c_2 \vec{v}_2 + \dots + c_k \vec{v}_k \text{ for } c_j \in \mathbb{R}.$$

Then

$$\begin{aligned}\langle \vec{v}, \vec{v}_i \rangle &= \langle c_1 \vec{v}_1 + c_2 \vec{v}_2 + \dots + c_k \vec{v}_k, \vec{v}_i \rangle \\ &= c_1 \langle \vec{v}_1, \vec{v}_i \rangle + c_2 \langle \vec{v}_2, \vec{v}_i \rangle + \dots + c_k \langle \vec{v}_k, \vec{v}_i \rangle \\ &= c_i \underbrace{\|\vec{v}_i\|^2}_{\text{non-zero}}\end{aligned}$$

In general

$$\langle \vec{v}, \vec{v}_j \rangle = c_j \|\vec{v}_j\|^2$$

Assume $\vec{v}_1, \dots, \vec{v}_k$ are linearly dependent. Then we can choose the constants such that $\vec{v} = 0$.

$$\begin{aligned}\text{Then } \langle \vec{v}, \vec{v}_j \rangle &= \langle 0, \vec{v}_j \rangle = 0 = c_j \|\vec{v}_j\|^2 \\ &\Rightarrow c_j = 0, \text{ for all } j.\end{aligned}$$

Or. The only solution to

$$(\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k) \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_k \end{pmatrix} = 0 \text{ is the}$$

zero solution! The vectors must be linearly independent.

Q: If $\{\vec{u}_1, \dots, \vec{u}_n\}$ is an orthonormal set in \mathbb{R}^n , what can be said about the matrix

$$A = (\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n)?$$

Why do we care about orthonormal bases? They are the generalization of the standard unit vectors $\{\vec{e}_j\}_{j=1}^n$. In some matrix computations using $\{\vec{e}_j\}_{j=1}^n$ is too difficult or too costly.

Orthonormal bases are customized to the inner product and for this reason they obey nice properties with respect to the corresponding norm.

Theorem: Let $\vec{u}_1, \dots, \vec{u}_n$ be an orthonormal basis for an inner product space V . Then one can write any element $\vec{v} \in V$ as a linear combination

$$\vec{v} = c_1 \vec{u}_1 + \dots + c_n \vec{u}_n,$$

such that

$$c_i = \langle \vec{v}, \vec{u}_i \rangle, \quad i = 1, \dots, n.$$

Furthermore,

$$\|\vec{v}\| = \sqrt{c_1^2 + \dots + c_n^2} = \sqrt{\sum_{i=1}^n \langle \vec{v}, \vec{u}_i \rangle^2}.$$

Proof: Since $\{\vec{u}_1, \dots, \vec{u}_n\}$ is a basis for V then

$$\vec{v} = c_1 \vec{u}_1 + \dots + c_n \vec{u}_n \text{ for some unique choice of } c_j, j=1, \dots, n.$$

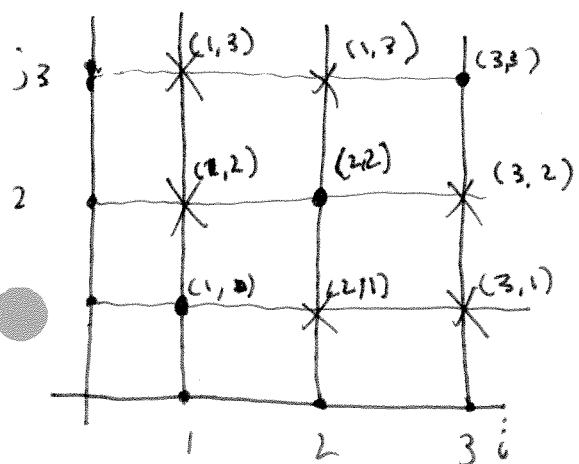
We have already seen that

$$\begin{aligned} \langle \vec{v}, \vec{u}_j \rangle &= c_j \|\vec{u}_j\|^2, \quad j=1, \dots, n \\ &= c_j, \quad j=1, \dots, n \quad \text{since } \|\vec{u}_j\|=1. \end{aligned}$$

For the second statement consider

$$\begin{aligned} \|\vec{v}\|^2 &= \langle \vec{v}, \vec{v} \rangle = \left\langle \sum_{j=1}^n c_j \vec{u}_j, \sum_{i=1}^n c_i \vec{u}_i \right\rangle \\ &= \sum_{j=1}^n \left\langle c_j \vec{u}_j, \sum_{i=1}^n c_i \vec{u}_i \right\rangle \\ &= \sum_{j=1}^n \sum_{i=1}^n \langle c_j \vec{u}_j, c_i \vec{u}_i \rangle = \sum_{j=1}^n \sum_{i=1}^n c_j c_i \langle \vec{u}_j, \vec{u}_i \rangle \end{aligned}$$

↗



Non zero only
when $i=j$

$$= \sum_{j=1}^n c_j^2 = \sum_{j=1}^n \langle \vec{v}, \vec{u}_j \rangle^2.$$

Ex Let $\{\vec{u}_1, \dots, \vec{u}_n\}$ be an orthonormal basis for \mathbb{R}^n .
and define

$$A = (\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n)$$

Write down the solution of

$$A \vec{x} = \vec{b}$$

for a general $\vec{b} \in \mathbb{R}^n$.

when ever I don't
specify, we use
the dot product.

This is asking you to find the constants x_1, \dots, x_n
so that

$$x_1 \vec{u}_1 + x_2 \vec{u}_2 + \dots + x_n \vec{u}_n = \vec{b}$$

$$\Rightarrow x_1 = \langle \vec{u}_1, \vec{b} \rangle, x_2 = \langle \vec{u}_2, \vec{b} \rangle, \dots$$

$$\Rightarrow \vec{x} = \begin{pmatrix} \langle \vec{u}_1, \vec{b} \rangle \\ \langle \vec{u}_2, \vec{b} \rangle \\ \vdots \\ \langle \vec{u}_n, \vec{b} \rangle \end{pmatrix}$$

Note $\langle \vec{u}_i, \vec{b} \rangle$ requires n multiplications and $n-1$ additions.
we do this n times.

$$\Rightarrow n^2 \text{ multiplications}\\ n^2 - n \text{ additions.}$$

This is the same as matrix vector multiplication!

The Gram-Schmidt Process

- The fundamental question here is how do we obtain an orthonormal basis from any other basis in an algorithmic way?

We start with a basis $\{\vec{w}_1, \dots, \vec{w}_n\}$ and vector-by-vector fix it up so that we obtain a basis $\{\vec{v}_1, \dots, \vec{v}_n\}$ that is orthonormal.

The process for doing this is called the Gram-Schmidt process.

- In our first run through we won't worry about normality since we know that it is easy to add normality to any basis by dividing by norms.

Step 1:

$$\text{Set } \vec{v}_1 = \vec{w}_1 \quad \begin{matrix} \leftarrow & \text{fix up } \vec{w}_2 \text{ with} \\ & \text{previously determined} \\ & \text{information} \end{matrix}$$

Step 2: Set $\vec{v}_2 = \vec{w}_2 - c \vec{v}_1$ $\begin{matrix} \uparrow & \text{to be determined.} \end{matrix}$

We want \vec{v}_1 and \vec{v}_2 to be orthogonal:

$$0 = \langle \vec{v}_1, \vec{v}_2 \rangle = \langle \vec{v}_1, \vec{w}_2 \rangle - c \langle \vec{v}_1, \vec{v}_1 \rangle \Rightarrow c = \frac{\langle \vec{v}_1, \vec{w}_2 \rangle}{\|\vec{v}_1\|^2}$$

Step 3 :

$$\vec{v}_3 = \vec{w}_3 - c_1 \vec{v}_1 - c_2 \vec{v}_2$$

Orthogonality:

$$\langle \vec{v}_1, \vec{v}_3 \rangle = \langle \vec{v}_1, \vec{w}_3 \rangle - c_1 \langle \vec{v}_1, \vec{v}_1 \rangle = 0$$

$$\langle \vec{v}_2, \vec{v}_3 \rangle = \langle \vec{v}_2, \vec{w}_3 \rangle - 0 - c_2 \langle \vec{v}_2, \vec{v}_2 \rangle$$

$$\Rightarrow c_1 = \frac{\langle \vec{v}_1, \vec{w}_3 \rangle}{\|\vec{v}_1\|^2}, \quad c_2 = \frac{\langle \vec{v}_2, \vec{w}_3 \rangle}{\|\vec{v}_2\|^2}$$

$$\vec{v}_3 = \vec{w}_3 - \left(\frac{\langle \vec{v}_1, \vec{w}_3 \rangle}{\|\vec{v}_1\|^2} \right) \vec{v}_1 - \left(\frac{\langle \vec{v}_2, \vec{w}_3 \rangle}{\|\vec{v}_2\|^2} \right) \vec{v}_2.$$

Step 4 :

$$\vec{v}_4 = \dots$$

In general

$$\vec{v}_k = \vec{w}_k - c_1 \vec{v}_1 - c_2 \vec{v}_2 - \dots - c_{k-1} \vec{v}_{k-1}$$

and inner products determine each c_j for $j = 1, \dots, k-1$.

Ex The vectors

$$\vec{w}_1 = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}, \vec{w}_2 = \begin{pmatrix} 1 \\ 0 \\ 2 \end{pmatrix}, \vec{w}_3 = \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix}.$$

form a basis of \mathbb{R}^3 . (construct an orthogonal basis).

$$\vec{v}_1 = \vec{w}_1.$$

$$\vec{v}_2 = \vec{w}_2 - c \vec{v}_1, \quad c = \frac{\vec{w}_2 \cdot \vec{v}_1}{\|\vec{v}_1\|^2} = \frac{-1}{3}$$

$$= \begin{pmatrix} 1 \\ 0 \\ 2 \end{pmatrix} - \left(-\frac{1}{3}\right) \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix} = \begin{pmatrix} 4/3 \\ 1/3 \\ 5/3 \end{pmatrix}$$

$$\vec{v}_3 = \vec{w}_3 - c_1 \vec{v}_1 - c_2 \vec{v}_2 \quad c_1 = \frac{\vec{w}_3 \cdot \vec{v}_1}{\|\vec{v}_1\|^2} = -1$$

$$c_2 = \frac{\vec{w}_3 \cdot \vec{v}_2}{\|\vec{v}_2\|^2} = 3/2$$

$$\vec{v}_3 = \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} - (-1) \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix} - 3/2 \begin{pmatrix} 1 \\ 0 \\ 2 \end{pmatrix}$$

$$= \begin{pmatrix} 1 \\ -3/2 \\ -1/2 \end{pmatrix}.$$

To make them orthonormal we would then divide them by their length:

$$\vec{u}_1 = \frac{\vec{v}_1}{\|\vec{v}_1\|} = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ -1/\sqrt{3} \end{pmatrix}, \quad \vec{u}_2 = \frac{\vec{v}_2}{\|\vec{v}_2\|} = \begin{pmatrix} 4/\sqrt{14} \\ 1/\sqrt{14} \\ 5/\sqrt{14} \end{pmatrix}, \quad \vec{u}_3 = \frac{\vec{v}_3}{\|\vec{v}_3\|} = \begin{pmatrix} 2/\sqrt{14} \\ -3/\sqrt{14} \\ -1/\sqrt{14} \end{pmatrix}.$$

We have already discussed how every finite dimensional vector space admits a basis. The Gram-Schmidt process allows one to construct an orthonormal basis if the underlying vector space is also an inner product space. This gives a beautiful constructive proof of the following theorem:

Theorem

Every non-zero finite-dimensional inner product space has an orthonormal basis.

As a final note we give the general Gram-Schmidt formula:

$$\vec{v}_k = \vec{w}_k - \sum_{j=1}^{k-1} \frac{\langle \vec{w}_k, \vec{v}_j \rangle}{\|\vec{v}_j\|^2} \vec{v}_j, \quad k=1, \dots, n.$$

Modifications and Generalization of Gram-Schmidt

Consider $\{\vec{w}_1, \dots, \vec{w}_n\}$ (some basis)

and $\{\vec{u}_1, \dots, \vec{u}_n\}$ the orthonormal basis from Gram-Schmidt, $\vec{u}_j = \frac{\vec{v}_j}{\|\vec{v}_j\|}$.

We can express

$$\vec{w}_1 = r_{11} \vec{u}_1$$

$$\vec{w}_2 = r_{12} \vec{u}_1 + r_{22} \vec{u}_2$$

$$\vec{w}_3 = r_{13} \vec{u}_1 + r_{23} \vec{u}_2 + r_{33} \vec{u}_3$$

⋮

$$\vec{w}_n = r_{1n} \vec{u}_1 + \dots + r_{nn} \vec{u}_n$$

It is straightforward to compute the r_{ij} 's once the other vectors are known..

$$\begin{cases} \langle \vec{w}_1, \vec{u}_1 \rangle = r_{11} \\ \langle \vec{w}_2, \vec{u}_1 \rangle = r_{12} \\ \langle \vec{w}_2, \vec{u}_2 \rangle = r_{22} \end{cases}$$

⋮

$$r_{ij} = \langle \vec{w}_j, \vec{u}_i \rangle$$

We know that the \vec{u}_j 's are orthonormal ...
 the question is: how does this show up?

$$\|\vec{w}_j\|^2 = \|\vec{r}_{1j}\vec{u}_1 + \dots + \vec{r}_{jj}\vec{u}_j\|^2 \\ = |\vec{r}_{1j}|^2 + \dots + |\vec{r}_{jj}|^2$$

We wish to determine the r_{ij} 's as we determine the \vec{u}_j , this way we can go back and forth between the two bases.

$$\vec{w}_1 = r_{11}\vec{u}_1 \quad \leftarrow \text{stage 1}$$

$$\vec{w}_{j-1} = r_{1,j-1}\vec{u}_1 + \dots + r_{j-1,j-1}\vec{u}_{j-1} \quad \leftarrow \text{stage } j-1$$

$$\vec{w}_j = r_{1j}\vec{u}_1 + \dots + r_{jj}\vec{u}_j \quad \leftarrow \text{stage } j.$$

At stage j we know

$$\vec{u}_1, \dots, \vec{u}_{j-1} \quad \text{but not } \vec{u}_j.$$

We find

$$r_{1j} = \langle \vec{w}_j, \vec{u}_1 \rangle$$

$$r_{2j} = \langle \vec{w}_j, \vec{u}_2 \rangle$$

\vdots

$$r_{j-1,j} = \langle \vec{w}_j, \vec{u}_{j-1} \rangle$$

What is r_{ij} ?

$$\|\vec{w}_j\|^2 = r_{1j}^2 + r_{2j}^2 + \dots + r_{j-1,j}^2 + r_{jj}^2$$

$$\Rightarrow r_{ij} = \sqrt{\|\vec{w}_j\|^2 - r_{1j}^2 - \dots - r_{j-1,j}^2}.$$

$$u_j = \frac{\vec{w}_j - r_{1j}\vec{u}_1 - \dots - r_{j-1,j}\vec{u}_{j-1}}{r_{jj}}$$

But... isn't the first version easier?

Yes, we know the r_{ij} 's, but this was a lot more work.

- Usefulness: Numerical computations? Not quite, the algorithm is unstable. Round off error will accumulate.

A numerically stable version of Gram-Schmidt:

$$\vec{u}_1 = \vec{w}_1 / \|\vec{w}_1\|$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{u}_1 \rangle \vec{u}_1 \quad (\text{for } k=2, \dots, n)$$

$$\vec{u}_2 = \vec{w}_2 / \|\vec{w}_2\|$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{u}_2 \rangle \vec{u}_2 \quad (\text{for } k=3, \dots, n)$$

$$\vec{u}_3 = \vec{w}_3 / \|\vec{w}_3\|.$$

:

In coding language:

Start with $\{\vec{w}_1, \vec{w}_2, \dots, \vec{w}_n\}$

$$\vec{w}_1 = \vec{w}_1 / \|\vec{w}_1\| \quad \% \text{ redefine}$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{w}_1 \rangle \vec{w}_1 \quad \text{for } k=2, \dots, n$$

$$\vec{w}_2 = \vec{w}_2 / \|\vec{w}_2\|$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{w}_2 \rangle \vec{w}_2 \quad \text{for } k=3, \dots, n.$$

We have seen three ways of performing Gram-Schmidt

$$1) \vec{v}_k = \vec{w}_k - \sum_{j=1}^{k-1} \frac{\langle \vec{w}_k, \vec{v}_j \rangle}{\| \vec{v}_j \|^2} v_j, \quad k=1, \dots, n$$

$$\vec{u}_j = \vec{v}_j / \| \vec{v}_j \|$$

$$2) \vec{w}_1 = r_{11} \vec{u}_1$$

$$\vec{w}_2 = r_{12} \vec{u}_1 + r_{22} \vec{u}_2$$

⋮

$$\vec{w}_n = r_{1n} \vec{u}_1 + \dots + r_{nn} \vec{u}_n$$

$$\left\{ \begin{array}{l} r_{ij} = \langle \vec{w}_j, \vec{u}_i \rangle, \quad i < j \\ r_{jj} = \sqrt{\| \vec{w}_j \|^2 - r_{1j}^2 - \dots - r_{j-1,j}^2} \end{array} \right.$$

$$3) \vec{u}_1 = \vec{w}_1 / \| \vec{w}_1 \|$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{u}_1 \rangle \vec{u}_1 \quad \text{for } k=2, \dots, n$$

$$\vec{u}_2 = \vec{w}_2 / \| \vec{w}_2 \|$$

$$\vec{w}_k = \vec{w}_k - \langle \vec{w}_k, \vec{u}_2 \rangle \vec{u}_2 \quad \text{for } k=3, \dots, n$$

$$\vec{u}_3 = \vec{w}_3 / \| \vec{w}_3 \|$$

Orthogonal Matrices

A definition:

A square matrix is called orthogonal if it satisfies

$$Q^T Q = I.$$

Thus $Q^T = Q^{-1}$.

Claim: A matrix Q is orthogonal if and only if its columns form an orthonormal basis with respect to the Euclidean dot product on \mathbb{R}^n .

Proof: First, let's look at a 2×2 matrix

$$Q = \begin{pmatrix} a & b \\ c & d \end{pmatrix}, \quad \vec{u}_1 = \begin{pmatrix} a \\ c \end{pmatrix}, \quad \vec{u}_2 = \begin{pmatrix} b \\ d \end{pmatrix}$$

$$\begin{aligned} Q^T Q &= \begin{pmatrix} a & c \\ b & d \end{pmatrix} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} a^2 + c^2 & ab + cd \\ ab + cd & c^2 + d^2 \end{pmatrix} \\ &= \begin{pmatrix} \vec{u}_1 \cdot \vec{u}_1 & \vec{u}_1 \cdot \vec{u}_2 \\ \vec{u}_2 \cdot \vec{u}_1 & \vec{u}_2 \cdot \vec{u}_2 \end{pmatrix} \end{aligned}$$

If $Q^T Q = I$ we get

$$\left. \begin{array}{l} \vec{u}_1 \cdot \vec{u}_1 = 1 \\ \vec{u}_2 \cdot \vec{u}_2 = 1 \\ \vec{u}_2 \cdot \vec{u}_1 = 0 \end{array} \right\}$$

orthonormal basis for \mathbb{R}^2 .

Facts:

- An orthogonal matrix has $\det Q = \pm 1$

$$\begin{aligned}\det I &= \det(Q^T \cdot Q) = \det Q^T \det Q \\ &= (\det Q)^2\end{aligned}$$

- The product of two orthogonal matrices is also an orthogonal matrix.

Ex: $Q = I$ is orthogonal

$$Q = \begin{pmatrix} 1/\sqrt{2} & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 \\ -1/\sqrt{2} & 0 & 1/\sqrt{2} \end{pmatrix}$$

The QR Factorization ("Gram-Schmidt w/ book keeping")

Let $\{\vec{w}_1, \dots, \vec{w}_n\}$ be a basis of \mathbb{R}^n and let $\{\vec{u}_1, \dots, \vec{u}_n\}$ be the orthonormal basis that results from the Gram-Schmidt process.

So +

$$A = (\vec{w}_1, \dots, \vec{w}_n), \quad Q = (\vec{u}_1, \dots, \vec{u}_n).$$

We want to know how A gets transformed into Q . Find R such that $A = QR$.

It turns out that R will be upper triangular.
What are the elements of R ?

We actually already looked at this:

We expressed:

$$\vec{w}_1 = r_{11} \vec{u}_1$$

$$\vec{w}_2 = r_{12} \vec{u}_2 + r_{22} \vec{u}_2$$

$$\vec{w}_3 = r_{13} \vec{u}_1 + r_{23} \vec{u}_2 + r_{33} \vec{u}_3$$

:

And found r_{ij} in terms of \vec{u}_i and \vec{w}_j .

$$r_{ij} = \langle \vec{w}_j, \vec{u}_i \rangle$$

This gives us a way to find them but how would we actually do this in practice?

Ex

$$\text{Set } A = \begin{pmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{pmatrix}$$

$$\text{Find } A = QR.$$

We will use

$$\vec{v}_k = \vec{w}_k - \sum_{j=1}^{k-1} \frac{\langle \vec{w}_k, \vec{v}_j \rangle}{\|\vec{v}_j\|^2} \vec{v}_j$$

OR, rearranging

$$\vec{w}_k = \vec{v}_k + \underbrace{\sum_{j=1}^{k-1} \frac{\langle \vec{w}_k, \vec{v}_j \rangle}{\|\vec{v}_j\|^2} \vec{v}_j}_{S_{jk}}$$

We will find an intermediate factorization

$$A = PS \quad \text{and then normalize}$$

$$(\vec{w}_1, \vec{w}_2, \dots, \vec{w}_n) = (\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n) \underbrace{\begin{pmatrix} 1 & S_{12} & S_{13} & \dots \\ 0 & 1 & S_{23} & \dots \\ 0 & 0 & 1 & \dots \end{pmatrix}}_S$$

P

$\vec{w}_1 = \vec{v}_1, \dots$

$$\begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix} \xrightarrow{\quad} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\vec{w}_1 = \vec{v}_1$$

$$\vec{v}_2 = \vec{w}_2 - \frac{\langle \vec{w}_2, \vec{v}_1 \rangle}{\|\vec{v}_1\|^2} \vec{v}_1$$

$$= \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} - \frac{4}{5} \begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix}$$

$$= \begin{pmatrix} -3/5 \\ 6/5 \\ 1 \end{pmatrix}$$

$$\vec{v}_3 = \vec{w}_3 - \frac{\langle \vec{w}_3, \vec{v}_1 \rangle}{\|\vec{v}_1\|^2} \vec{v}_1 - \frac{\langle \vec{w}_3, \vec{v}_2 \rangle}{\|\vec{v}_2\|^2} \vec{v}_2$$

$$= \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix} - \frac{1}{5} \begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix} - \frac{16/5}{9/25 + 3/25} \begin{pmatrix} -3/5 \\ 6/5 \\ 1 \end{pmatrix}$$

$$= \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix} - \frac{1}{5} \begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix} - \frac{16/5}{70/25} \begin{pmatrix} -3/5 \\ 6/5 \\ 1 \end{pmatrix}$$

$$= \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix} - \left(\frac{1}{5} \right) \begin{pmatrix} 2 \\ 1 \\ 0 \end{pmatrix} - \frac{8}{7} \begin{pmatrix} -3/5 \\ 6/5 \\ 1 \end{pmatrix}$$

$$= \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix} + \begin{pmatrix} -2/5 \\ -1/5 \\ 0 \end{pmatrix} + 8 \begin{pmatrix} 24/35 \\ -48/35 \\ -40/35 \end{pmatrix}$$

$$= \begin{pmatrix} 10/35 \\ -20/35 \\ 30/35 \end{pmatrix}$$

$$\begin{pmatrix} 2 & -3/5 & 10/35 \\ 1 & 6/5 & -20/35 \\ 0 & 1 & 30/35 \end{pmatrix}, \quad \begin{pmatrix} 1 & 4/5 & 11/5 \\ 0 & 1 & 8/7 \\ 0 & 0 & 1 \end{pmatrix}$$

Now, we have a factorization

$$A = PS.$$

But P is not orthogonal.

Compute

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} \frac{1}{\|c_1\|} & 0 \\ 0 & \frac{1}{\|c_2\|} \end{pmatrix} = \begin{pmatrix} a/\|c_1\| & b/\|c_2\| \\ c/\|c_1\| & d/\|c_2\| \end{pmatrix}$$

multiples columns.



$$\text{So } Q = P \begin{pmatrix} \frac{1}{\|\vec{v}_1\|} & 0 & 0 \\ 0 & \frac{1}{\|\vec{v}_2\|} & 0 \\ 0 & 0 & \frac{1}{\|\vec{v}_3\|} \end{pmatrix} \quad \text{B orthogonal!}$$

" D

Write

$$A = \underbrace{P}_{Q} \underbrace{D}_{R} \underbrace{D^{-1}S}_{R}$$

multiples rows!

Compute

$$\begin{pmatrix} c_1 & 0 \\ 0 & c_2 \end{pmatrix} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} c_1 a & c_1 b \\ c_2 a & c_2 b \end{pmatrix}$$



Conclusion?

Divide the columns of P by the norms $\Rightarrow Q$

Multiply the rows of S by the norms $\Rightarrow R$

$$\begin{pmatrix} 2 & -3/5 & 16/35 \\ 1 & 6/5 & -20/35 \\ 0 & 1 & 30/35 \end{pmatrix}, \quad \begin{pmatrix} 1 & 4/5 & 1/5 \\ 0 & 1 & 8/7 \\ 0 & 0 & 1 \end{pmatrix}$$

\downarrow

$$\|\vec{v}_1\| = \sqrt{5} \quad \|\vec{v}_2\| = \sqrt{\frac{70}{5}} = \sqrt{\frac{14}{5}} \quad \|\vec{v}_3\| = 2\sqrt{\frac{2}{7}}$$

$$Q = \begin{pmatrix} \frac{2}{\sqrt{5}} & -\frac{3}{\sqrt{70}} & \frac{1}{\sqrt{14}} \\ \frac{1}{\sqrt{5}} & \frac{6}{\sqrt{70}} & -\frac{\sqrt{2}}{\sqrt{7}} \\ 0 & \frac{5}{\sqrt{70}} & \frac{3}{\sqrt{14}} \end{pmatrix}, \quad R = \begin{pmatrix} \sqrt{5} & \frac{4}{\sqrt{5}} & \frac{1}{\sqrt{5}} \\ 0 & \frac{\sqrt{14}}{5} & \frac{8}{\sqrt{35}} \\ 0 & 0 & 2\sqrt{\frac{2}{7}} \end{pmatrix}$$

Remark : There is no reason that we have to have 3 vectors in the previous problem :

If $A = \begin{pmatrix} 2 & 1 \\ 1 & 2 \\ 0 & 1 \end{pmatrix}$

then $A = \begin{pmatrix} 2 & -3/\sqrt{5} \\ 1 & 6/\sqrt{5} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 4/\sqrt{5} \\ 0 & 1 \end{pmatrix}$

 $= \begin{pmatrix} 2/\sqrt{5} & -3/\sqrt{70} \\ 1/\sqrt{5} & 6/\sqrt{70} \\ 0 & 5/\sqrt{70} \end{pmatrix} \begin{pmatrix} \sqrt{5} & 4/\sqrt{5} \\ 0 & \sqrt{14}/5 \end{pmatrix}$

"
Q

"
R

Note

that $\underset{\substack{\uparrow \\ 2+3}}{Q^T} \underset{\substack{\uparrow \\ 3+2}}{Q} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$.

An application of QR:

Consider finding a least-squares solution of

$A\vec{x} = \vec{b}$.

Assuming A has rank n.

$m \times n$ $n \times 1$ $m \times 1$

Assume we know

$$A = QR$$

$m \times n \quad m \times n \quad n \times n$

We need to solve the normal equations.

$$A^T A \vec{x} = A^T \vec{b}$$

$$(QR)^T QR \vec{x} = A^T \vec{b}$$

$$\begin{matrix} R^T Q^T Q R \vec{x} = A^T \vec{b} \\ \begin{matrix} n \times n & n \times m & m \times n & n \times n \\ \swarrow & \downarrow & \searrow & \\ n \times n & \text{id matrix} \end{matrix} \end{matrix}$$

$$R^T R \vec{x} = A^T \vec{b} \quad \leftarrow \text{this can be solved by forward/back substitution.}$$

$\begin{matrix} \uparrow & \uparrow \\ \text{lower triangular} & \text{upper triangular} \end{matrix}$

Moral of the story: QR factorization gives the LU factorization of $A^T A$.