

# Mathematics for Computer Science

## Linear Algebra

### Lecture 16: The Gram-Schmidt process and QR-decomposition

Andrei Krokhin

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## Reminder from the last lecture

- An **inner product space** is a (real) vector space  $V$  equipped with an **inner product** — a function that associates to each pair  $\mathbf{u}, \mathbf{v} \in V$  a real number denoted  $\langle \mathbf{u}, \mathbf{v} \rangle \in \mathbb{R}$ . This function must satisfy four axioms:

- Symmetry, additivity, homogeneity, positivity.

- The **norm** of a vector is defined as  $\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$ .

A vector  $\mathbf{v}$  with  $\|\mathbf{v}\| = 1$  is called a **unit vector**. Each non-zero vector can be **normalised** (scaled to become a unit vector):  $\mathbf{v} \mapsto \frac{1}{\|\mathbf{v}\|} \mathbf{v}$ .

- Vectors  $\mathbf{u}$  and  $\mathbf{v}$  are called **orthogonal** if  $\langle \mathbf{u}, \mathbf{v} \rangle = 0$ .
- For a subspace  $W$  of an inner product space  $V$ , can define the **orthogonal complement**

$$W^\perp = \{\mathbf{x} \in V \mid \langle \mathbf{u}, \mathbf{x} \rangle = 0 \text{ for all } \mathbf{u} \in W\}$$

- A vector space can be equipped with different inner products — the notions of norm and orthogonality depend on the choice of inner product.

# Contents for today's lecture

- Orthogonal and orthonormal bases in an inner vector space
- Constructing such bases - the Gram-Schmidt process
- QR-decomposition of matrices

# Orthogonal and orthonormal sets of vectors

## Definition

A set of vectors in an inner product space is called **orthogonal** if all pairs of distinct vectors in it are orthogonal. An orthogonal set consisting of unit vectors is called **orthonormal**.

Example in  $\mathbb{R}^3$  (with the Euclidean inner product): Let

$$\mathbf{v}_1 = (0, 1, 0), \mathbf{v}_2 = (1, 0, 1), \mathbf{v}_3 = (1, 0, -1).$$

The set  $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$  is orthogonal, since  $\langle \mathbf{v}_1, \mathbf{v}_2 \rangle = \langle \mathbf{v}_1, \mathbf{v}_3 \rangle = \langle \mathbf{v}_2, \mathbf{v}_3 \rangle = 0$ .

The norms of the vectors are:

$$\|\mathbf{v}_1\| = 1, \|\mathbf{v}_2\| = \sqrt{2}, \|\mathbf{v}_3\| = \sqrt{2}.$$

By normalising (i.e. setting  $\mathbf{q}_i = \frac{1}{\|\mathbf{v}_i\|} \mathbf{v}_i$ ), we get an orthonormal set  $\{\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3\}$

$$\mathbf{q}_1 = (0, 1, 0), \mathbf{q}_2 = \left(\frac{1}{\sqrt{2}}, 0, \frac{1}{\sqrt{2}}\right), \mathbf{q}_3 = \left(\frac{1}{\sqrt{2}}, 0, -\frac{1}{\sqrt{2}}\right).$$

# Orthogonal sets are linearly independent

## Theorem

If  $S = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$  is an orthogonal set of non-zero vectors in an inner product space then  $S$  is linearly independent.

## Proof.

Assume that  $k_1\mathbf{v}_1 + \dots + k_n\mathbf{v}_n = \mathbf{0}$  and prove that  $k_1 = \dots = k_n = 0$ .

Pick any  $\mathbf{v}_i$  and take the product of both sides of the above equation with this  $\mathbf{v}_i$ :

$$\langle k_1\mathbf{v}_1 + \dots + k_n\mathbf{v}_n, \mathbf{v}_i \rangle = \langle \mathbf{0}, \mathbf{v}_i \rangle = 0$$

By using the linearity (i.e. additivity + homogeneity) of the inner product, as well as orthogonality of  $S$  (i.e.  $\langle \mathbf{v}_j, \mathbf{v}_i \rangle = 0$  for  $j \neq i$ ), we get

$$\langle k_1\mathbf{v}_1 + \dots + k_n\mathbf{v}_n, \mathbf{v}_i \rangle = k_1\langle \mathbf{v}_1, \mathbf{v}_i \rangle + \dots + k_n\langle \mathbf{v}_n, \mathbf{v}_i \rangle = k_i\langle \mathbf{v}_i, \mathbf{v}_i \rangle.$$

Thus,  $k_i\langle \mathbf{v}_i, \mathbf{v}_i \rangle = 0$ , and, since  $\mathbf{v}_i$  is non-zero, it follows that  $k_i = 0$ . □

## Orthogonal and orthonormal bases

An orthogonal (resp. orthonormal) basis in an inner product space is a basis, which is an orthogonal (resp. orthonormal) set. For example,

$\{\mathbf{v}_1 = (0, 1, 0), \mathbf{v}_2 = (\frac{1}{\sqrt{2}}, 0, \frac{1}{\sqrt{2}}), \mathbf{v}_3 = (\frac{1}{\sqrt{2}}, 0, -\frac{1}{\sqrt{2}})\}$  is an orthonormal basis in  $\mathbb{R}^3$

### Theorem

*If  $S = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$  is an orthogonal basis in inner product space  $V$  then for any  $\mathbf{u}$*

$$\mathbf{u} = \frac{\langle \mathbf{u}, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 + \frac{\langle \mathbf{u}, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 + \dots + \frac{\langle \mathbf{u}, \mathbf{v}_n \rangle}{\|\mathbf{v}_n\|^2} \mathbf{v}_n.$$

*Moreover, if  $S$  is an orthonormal basis in  $V$  then*

$$\mathbf{u} = \langle \mathbf{u}, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{u}, \mathbf{v}_2 \rangle \mathbf{v}_2 + \dots + \langle \mathbf{u}, \mathbf{v}_n \rangle \mathbf{v}_n.$$

### Proof.

If  $\mathbf{u} = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \dots + c_n \mathbf{v}_n$  then, since  $\langle \mathbf{v}_j, \mathbf{v}_i \rangle = 0$  for all  $j \neq i$ , we have that, for each  $i$ ,  $\langle \mathbf{u}, \mathbf{v}_i \rangle = c_i \langle \mathbf{v}_i, \mathbf{v}_i \rangle = c_i \|\mathbf{v}_i\|^2$ , so  $c_i = \frac{\langle \mathbf{u}, \mathbf{v}_i \rangle}{\|\mathbf{v}_i\|^2}$ , as required.  $\square$

# Orthogonal projections

## Theorem (Projection Theorem)

If  $W$  is a subspace in a finite-dimensional inner product space  $V$  then every vector  $\mathbf{u} \in V$  can be uniquely expressed as  $\mathbf{u} = \mathbf{w}_1 + \mathbf{w}_2$  where  $\mathbf{w}_1 \in W$  and  $\mathbf{w}_2 \in W^\perp$ .

If  $\mathbf{u}, \mathbf{w}_1$  and  $\mathbf{w}_2$  are as above then  $\mathbf{w}_1$  is the **orthogonal projection** of  $\mathbf{u}$  onto  $W$ .

Notation:  $\mathbf{w}_1 = \text{proj}_W \mathbf{u}$  and  $\mathbf{w}_2 = \text{proj}_{W^\perp} \mathbf{u}$ .

How to compute orthogonal projections? Pretty much the same idea as before.

If  $\{\mathbf{v}_1, \dots, \mathbf{v}_r\}$  is an orthogonal basis for  $W$  and  $\mathbf{w}_1 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \dots + c_r \mathbf{v}_r$ , use  $\langle \mathbf{u}, \mathbf{v}_i \rangle = \langle \mathbf{w}_1 + \mathbf{w}_2, \mathbf{v}_i \rangle = \langle \mathbf{w}_1, \mathbf{v}_i \rangle + \langle \mathbf{w}_2, \mathbf{v}_i \rangle = \langle \mathbf{w}_1, \mathbf{v}_i \rangle = c_i \langle \mathbf{v}_i, \mathbf{v}_i \rangle$  to find the  $c_i$ 's:

$$\text{proj}_W \mathbf{u} = \frac{\langle \mathbf{u}, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 + \frac{\langle \mathbf{u}, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 + \dots + \frac{\langle \mathbf{u}, \mathbf{v}_r \rangle}{\|\mathbf{v}_r\|^2} \mathbf{v}_r.$$

Moreover, if  $\{\mathbf{v}_1, \dots, \mathbf{v}_r\}$  is an orthonormal basis in  $W$  then

$$\text{proj}_W \mathbf{u} = \langle \mathbf{u}, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{u}, \mathbf{v}_2 \rangle \mathbf{v}_2 + \dots + \langle \mathbf{u}, \mathbf{v}_r \rangle \mathbf{v}_r.$$

# The Gram-Schmidt (orthogonalisation) process

## Theorem

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

- Let  $W$  be a subspace of  $V$  and let  $\{\mathbf{u}_1, \dots, \mathbf{u}_n\}$  be a basis of  $W$ .  
Consider the subspaces  $W_r = \text{span}(\mathbf{u}_1, \dots, \mathbf{u}_r)$ ,  $r = 1, \dots, n$ , in  $W$ .  
Note that  $W_1 \subseteq W_2 \subseteq \dots \subseteq W_n = W$ .
- The **Gram-Schmidt process** inductively constructs orthogonal bases for the subspaces  $W_i$ , eventually constructing an orthogonal basis for  $W_n = W$ .  
Once we have an orthogonal basis for  $W$ , we can normalise all vectors in it.

The Gram Schmidt process:

Step 1. Let  $\mathbf{v}_1 = \mathbf{u}_1$ . Clearly,  $\{\mathbf{v}_1\}$  is an orthogonal basis for  $W_1 = \text{span}(\mathbf{u}_1)$ .

Step  $r$  ( $2 \leq r \leq n$ ). Assuming that we have an orthogonal basis  $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}\}$  for  $W_{r-1}$ , add a vector  $\mathbf{v}_r$  to it to get an orthogonal basis for  $W_r$ .



# The Gram-Schmidt (orthogonalisation) process

Step  $r$ : If  $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}\}$  is an orthogonal basis for  $W_{r-1} = \text{span}(\mathbf{u}_1, \dots, \mathbf{u}_{r-1})$ , find a vector  $\mathbf{v}_r$  such that  $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}, \mathbf{v}_r\}$  is an orthogonal basis for  $W_r$ .

Apply the Projection theorem to  $\mathbf{u}_r \in W_r$  and  $W_{r-1}$  (as a subspace of  $W_r$ ):

$$\mathbf{u}_r = \text{proj}_{W_{r-1}} \mathbf{u}_r + \text{proj}_{W_{r-1}^\perp} \mathbf{u}_r.$$

(Note that the orthogonal complement  $W_{r-1}^\perp$  here is taken in  $W_r$ ).

Recall that, since  $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}\}$  is an orthogonal basis for  $W_{r-1}$ , we have

$$\text{proj}_{W_{r-1}} \mathbf{u}_r = \frac{\langle \mathbf{u}_r, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 + \frac{\langle \mathbf{u}_r, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 + \dots + \frac{\langle \mathbf{u}_r, \mathbf{v}_{r-1} \rangle}{\|\mathbf{v}_{r-1}\|^2} \mathbf{v}_{r-1}.$$

Set

$$\mathbf{v}_r = \text{proj}_{W_{r-1}^\perp} \mathbf{u}_r = \mathbf{u}_r - \frac{\langle \mathbf{u}_r, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 - \frac{\langle \mathbf{u}_r, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 - \dots - \frac{\langle \mathbf{u}_r, \mathbf{v}_{r-1} \rangle}{\|\mathbf{v}_{r-1}\|^2} \mathbf{v}_{r-1}.$$

Since  $\mathbf{v}_r \in W_{r-1}^\perp$ , the set  $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}, \mathbf{v}_r\}$  is orthogonal (and so linearly indep.)

$$W_r = \text{span}(\mathbf{u}_1, \dots, \mathbf{u}_{r-1}, \mathbf{u}_r) = \text{span}(\mathbf{v}_1, \dots, \mathbf{v}_{r-1}, \mathbf{u}_r) = \text{span}(\mathbf{v}_1, \dots, \mathbf{v}_{r-1}, \mathbf{v}_r).$$

# The Gram-Schmidt process: Summary

To convert a (linearly independent) set  $S = \{\mathbf{u}_1, \dots, \mathbf{u}_n\}$  into an orthogonal basis for  $\text{span}(S)$ , do the following:

Step 1.  $\mathbf{v}_1 = \mathbf{u}_1$ .

Step 2.  $\mathbf{v}_2 = \mathbf{u}_2 - \text{proj}_{W_1} \mathbf{u}_2 = \mathbf{u}_2 - \frac{\langle \mathbf{u}_2, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1$ .

Step 3.  $\mathbf{v}_3 = \mathbf{u}_3 - \text{proj}_{W_2} \mathbf{u}_3 = \mathbf{u}_3 - \frac{\langle \mathbf{u}_3, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 - \frac{\langle \mathbf{u}_3, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2$

Step 4.  $\mathbf{v}_4 = \mathbf{u}_4 - \text{proj}_{W_3} \mathbf{u}_4 = \mathbf{u}_4 - \frac{\langle \mathbf{u}_4, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 - \frac{\langle \mathbf{u}_4, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 - \frac{\langle \mathbf{u}_4, \mathbf{v}_3 \rangle}{\|\mathbf{v}_3\|^2} \mathbf{v}_3$

$\vdots$

(continue for  $n$  steps)

Optional step. Normalise all vectors  $\mathbf{v}_i$  if an orthonormal basis is needed.

## Example: Using the Gram-Schmidt process

Task: Consider  $\mathbb{R}^3$  with the Euclidean inner product. Find an orthonormal basis of  $W = \text{span}(\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3)$  where  $\mathbf{u}_1 = (1, 1, 1)$ ,  $\mathbf{u}_2 = (0, 1, 1)$ ,  $\mathbf{u}_3 = (0, 0, 1)$ .

Step 1.  $\mathbf{v}_1 = \mathbf{u}_1 = (1, 1, 1)$ .

Step 2.  $\mathbf{v}_2 = \mathbf{u}_2 - \text{proj}_{W_1} \mathbf{u}_2 = \mathbf{u}_2 - \frac{\langle \mathbf{u}_2, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 =$

$$(0, 1, 1) - \frac{2}{3}(1, 1, 1) = \left(-\frac{2}{3}, \frac{1}{3}, \frac{1}{3}\right).$$

Step 3.  $\mathbf{v}_3 = \mathbf{u}_3 - \text{proj}_{W_2} \mathbf{u}_3 = \mathbf{u}_3 - \frac{\langle \mathbf{u}_3, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 - \frac{\langle \mathbf{u}_3, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2 =$

$$(0, 0, 1) - \frac{1}{3}(1, 1, 1) - \frac{1/3}{2/3} \left(-\frac{2}{3}, \frac{1}{3}, \frac{1}{3}\right) = \left(0, -\frac{1}{2}, \frac{1}{2}\right).$$

$\{\mathbf{v}_1 = (1, 1, 1), \mathbf{v}_2 = (-\frac{2}{3}, \frac{1}{3}, \frac{1}{3}), \mathbf{v}_3 = (0, -\frac{1}{2}, \frac{1}{2})\}$  is an orthogonal basis for  $W$ .

Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \frac{\sqrt{6}}{3}$ ,  $\|\mathbf{v}_3\| = \frac{1}{\sqrt{2}}$ , we have an orthonormal basis for  $W$ :

$$\{\mathbf{q}_1 = \frac{1}{\|\mathbf{v}_1\|} \mathbf{v}_1 = \left(\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}\right), \mathbf{q}_2 = \left(-\frac{2}{\sqrt{6}}, \frac{1}{\sqrt{6}}, \frac{1}{\sqrt{6}}\right), \mathbf{q}_3 = \left(0, -\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right)\}$$

## Example: Using the Gram-Schmidt process

Consider the space  $C[-1, 1]$ . Find an orthogonal basis of  $W = \text{span}(\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3)$  where  $\mathbf{u}_1 = 1$ ,  $\mathbf{u}_2 = x$ ,  $\mathbf{u}_3 = x^2$ .

Step 1.  $\mathbf{v}_1 = \mathbf{u}_1 = 1$ .

Step 2.  $\mathbf{v}_2 = \mathbf{u}_2 - \text{proj}_{W_1} \mathbf{u}_2 = \mathbf{u}_2 - \frac{\langle \mathbf{u}_2, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1$ . We have

$$\langle \mathbf{u}_2, \mathbf{v}_1 \rangle = \int_{-1}^1 x \, dx = 0 \quad \text{and} \quad \|\mathbf{v}_1\|^2 = \langle \mathbf{v}_1, \mathbf{v}_1 \rangle = \int_{-1}^1 1 \, dx = 2$$

so  $\mathbf{v}_2 = \mathbf{u}_2 - 0\mathbf{v}_1 = x$ .

Step 3.  $\mathbf{v}_3 = \mathbf{u}_3 - \text{proj}_{W_2} \mathbf{u}_3 = \mathbf{u}_3 - \frac{\langle \mathbf{u}_3, \mathbf{v}_1 \rangle}{\|\mathbf{v}_1\|^2} \mathbf{v}_1 - \frac{\langle \mathbf{u}_3, \mathbf{v}_2 \rangle}{\|\mathbf{v}_2\|^2} \mathbf{v}_2$ . We have

$$\langle \mathbf{u}_3, \mathbf{v}_1 \rangle = \int_{-1}^1 x^2 \, dx = \frac{2}{3} \quad \text{and} \quad \langle \mathbf{u}_3, \mathbf{v}_2 \rangle = \int_{-1}^1 x^3 \, dx = 0.$$

Hence,  $\mathbf{v}_3 = x^2 - \frac{2/3}{2} \mathbf{v}_1 - 0\mathbf{v}_2 = x^2 - \frac{1}{3}$ .

So,  $\{\mathbf{v}_1 = 1, \mathbf{v}_2 = x, \mathbf{v}_3 = x^2 - \frac{1}{3}\}$  is an orthogonal basis for  $W$ .

# Extending an orthogonal set to an orthogonal basis

## Theorem

If  $V$  is a finite-dimensional inner product space then

- 1 Any orthogonal set of vectors in  $V$  can be extended to an orthogonal basis.
- 2 Any orthonormal set of vectors in  $V$  can be extended to an orthonormal basis.

## Proof.

Let  $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$  be an orthogonal set in  $V$  and  $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_{k+n}\}$  some basis in  $V$ .

- Apply Gram-Schmidt to the set  $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_{k+n}\}$ .
- Since  $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$  is an orthogonal set, we will have  $\mathbf{v}_i = \mathbf{u}_i$  for  $1 \leq i \leq k$ .
- If  $\mathbf{v}_r = \mathbf{0}$  at any Step  $r$  (with  $r > k$ ), do not add it to the output set.

(This happens iff  $\mathbf{u}_r \in \text{span}(\mathbf{u}_1, \dots, \mathbf{u}_{r-1})$ , i.e. if  $W_{r-1} = W_r$ .)

The final set will extend  $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ , it will be orthogonal (and hence linearly independent), and its span will be  $\text{span}(\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_{k+n}) = V$ .

For item (2), normalise all vectors in the final set.



## QR-decomposition

Let  $A$  be an  $m \times n$  matrix with linearly independent columns  $\mathbf{u}_1, \dots, \mathbf{u}_n$

Let  $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$  be the orthonormal set obtained by applying Gram-Schmidt to  $\{\mathbf{u}_1, \dots, \mathbf{u}_n\}$ . How does  $A = [\mathbf{u}_1 | \dots | \mathbf{u}_n]$  relate to the matrix  $Q = [\mathbf{q}_1 | \dots | \mathbf{q}_n]$  ?

Since  $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$  is an orthonormal basis for  $\text{span}(\mathbf{u}_1, \dots, \mathbf{u}_n)$ , we have

$$\begin{aligned}\mathbf{u}_1 &= \langle \mathbf{u}_1, \mathbf{q}_1 \rangle \mathbf{q}_1 + \langle \mathbf{u}_1, \mathbf{q}_2 \rangle \mathbf{q}_2 + \dots + \langle \mathbf{u}_1, \mathbf{q}_n \rangle \mathbf{q}_n \\ \mathbf{u}_2 &= \langle \mathbf{u}_2, \mathbf{q}_1 \rangle \mathbf{q}_1 + \langle \mathbf{u}_2, \mathbf{q}_2 \rangle \mathbf{q}_2 + \dots + \langle \mathbf{u}_2, \mathbf{q}_n \rangle \mathbf{q}_n \\ &\vdots \\ \mathbf{u}_n &= \langle \mathbf{u}_n, \mathbf{q}_1 \rangle \mathbf{q}_1 + \langle \mathbf{u}_n, \mathbf{q}_2 \rangle \mathbf{q}_2 + \dots + \langle \mathbf{u}_n, \mathbf{q}_n \rangle \mathbf{q}_n\end{aligned}$$

or, in the matrix form,

$$A = [\mathbf{u}_1 | \dots | \mathbf{u}_n] = [\mathbf{q}_1 | \dots | \mathbf{q}_n] \begin{pmatrix} \langle \mathbf{u}_1, \mathbf{q}_1 \rangle & \langle \mathbf{u}_2, \mathbf{q}_1 \rangle & \dots & \langle \mathbf{u}_n, \mathbf{q}_1 \rangle \\ \langle \mathbf{u}_1, \mathbf{q}_2 \rangle & \langle \mathbf{u}_2, \mathbf{q}_2 \rangle & \dots & \langle \mathbf{u}_n, \mathbf{q}_2 \rangle \\ \vdots & \vdots & \vdots & \vdots \\ \langle \mathbf{u}_1, \mathbf{q}_n \rangle & \langle \mathbf{u}_2, \mathbf{q}_n \rangle & \dots & \langle \mathbf{u}_n, \mathbf{q}_n \rangle \end{pmatrix} = QR.$$

## QR-decomposition

What can we say about the matrix  $R$ ?

From Gram-Schmidt, for each  $j \geq 2$ ,  $\mathbf{q}_j$  is orthogonal to  $\mathbf{u}_1, \dots, \mathbf{u}_{j-1}$ . Hence  $R$  is

$$\begin{pmatrix} \langle \mathbf{u}_1, \mathbf{q}_1 \rangle & \langle \mathbf{u}_2, \mathbf{q}_1 \rangle & \cdots & \langle \mathbf{u}_n, \mathbf{q}_1 \rangle \\ \langle \mathbf{u}_1, \mathbf{q}_2 \rangle & \langle \mathbf{u}_2, \mathbf{q}_2 \rangle & \cdots & \langle \mathbf{u}_n, \mathbf{q}_2 \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \mathbf{u}_1, \mathbf{q}_n \rangle & \langle \mathbf{u}_2, \mathbf{q}_n \rangle & \cdots & \langle \mathbf{u}_n, \mathbf{q}_n \rangle \end{pmatrix} = \begin{pmatrix} \langle \mathbf{u}_1, \mathbf{q}_1 \rangle & \langle \mathbf{u}_2, \mathbf{q}_1 \rangle & \cdots & \langle \mathbf{u}_n, \mathbf{q}_1 \rangle \\ 0 & \langle \mathbf{u}_2, \mathbf{q}_2 \rangle & \cdots & \langle \mathbf{u}_n, \mathbf{q}_2 \rangle \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \langle \mathbf{u}_n, \mathbf{q}_n \rangle \end{pmatrix}.$$

From Gram-Schmidt,  $\langle \mathbf{u}_i, \mathbf{q}_i \rangle = \langle \mathbf{u}_i, \frac{1}{\|\mathbf{v}_i\|} \mathbf{v}_i \rangle = \frac{1}{\|\mathbf{v}_i\|} \langle \mathbf{u}_i, \mathbf{v}_i \rangle = \frac{1}{\|\mathbf{v}_i\|} \langle \mathbf{v}_i, \mathbf{v}_i \rangle > 0$ .

### Theorem (QR-decomposition)

If  $A$  is an  $m \times n$  matrix with linearly independent column vectors, then it can be factored as

$$A = QR$$

where  $Q$  has orthonormal columns and  $R$  is an invertible upper triangular matrix.

For  $m = n$ , this theorem says that every invertible matrix has a QR-decomposition.

# What we learnt today

- Orthogonal and orthonormal bases in an inner vector space
- Constructing such bases - the Gram-Schmidt process
- QR-decomposition of matrices

Next time:

- Least squares - solving inconsistent linear systems