# Mathematics for Computer Science Linear Algebra

# Lecture 10: The fundamental spaces of a matrix

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## Reminder from the previous lecture

- Vectors  $\mathbf{v}_1, \dots, \mathbf{v}_r$  are linearly independent if  $k_1 \mathbf{v}_1 + k_2 \mathbf{v}_2 + \dots + k_r \mathbf{v}_r = \mathbf{0}$  implies that  $k_1 = \dots = k_r = 0$ . Otherwise, they are linearly dependent.
- A set B of vectors in a vector space V is a basis for V if (1) B is linearly independent and (2) B spans V.
- We have  $\{\mathbf v_1,\ldots,\mathbf v_n\}$  is a basis in  $\mathbb R^n$  iff  $det([\mathbf v_1|\ldots|\mathbf v_n])\neq 0$ .
- All bases of a finite-dimensional vector space V have the same number of vectors. This number is called the dimension of V and denoted by dim(V).

## Contents for today's lecture

- Row, column, and null spaces of a matrix
- How to find bases in these spaces
- The rank of a matrix

# Row space, column space, and null space of a matrix

### Definition

Let A be an  $m \times n$  matrix.

The row space of A is the subspace of  $\mathbb{R}^n$  spanned by the row vectors of A. The column space of A is the subspace of  $\mathbb{R}^m$  spanned by the column vectors of A. The null space of A is the subspace of  $\mathbb{R}^n$  equal to the solution space of  $A\mathbf{x} = \mathbf{0}$ .

Example: let

$$A = \left(\begin{array}{ccc} 2 & 1 & 0 \\ 3 & -1 & 4 \end{array}\right)$$

The row vectors of A are

$$\mathbf{r}_1 = (2, 1, 0)$$
 and  $\mathbf{r}_2 = (3, -1, 4)$ .

The column vectors of A are

$$\boldsymbol{c}_1 = \left( \begin{array}{c} 2 \\ 3 \end{array} \right), \boldsymbol{c}_2 = \left( \begin{array}{c} 1 \\ -1 \end{array} \right), \text{ and } \boldsymbol{c}_3 = \left( \begin{array}{c} 0 \\ 4 \end{array} \right).$$

## Elementary row operations and the row space

#### Lemma

Elementary row operations do not change the row space of a matrix.

### Proof.

For any (row) vectors  $\mathbf{r}_i$  and  $\mathbf{r}_j$  from a matrix A, and any scalar  $k \neq 0$ , we have

$$span(\mathbf{r}_i, \mathbf{r}_j) = span(\mathbf{r}_j, \mathbf{r}_i) = span(k\mathbf{r}_i, \mathbf{r}_j) = span(\mathbf{r}_i, \mathbf{r}_j + k\mathbf{r}_i).$$

Clearly, the equalities hold if we add the remaining row vectors of A to each span:

$$span(\mathbf{r}_i, \mathbf{r}_j, \mathbf{r}_1, \ldots) = \ldots = span(k\mathbf{r}_i, \mathbf{r}_j, \mathbf{r}_1, \ldots) = span(\mathbf{r}_i, \mathbf{r}_j + k\mathbf{r}_i, \mathbf{r}_1, \ldots).$$

So, any elementary row operation does not change the row space of A.

## Elementary row operations and the row space

#### Lemma

If R is a matrix in row echelon form, then its non-zero rows form a basis for its row space.

These rows obviously span the row space, need to check linear independence.

The idea of a proof on an example: let  $\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3$  be the first three rows of the following matrix:

Let 
$$k_1\mathbf{r}_1 + k_2\mathbf{r}_2 + k_3\mathbf{r}_3 = \mathbf{0}$$
. Since  $k_1\mathbf{r}_1 + k_2\mathbf{r}_2 + k_3\mathbf{r}_3 = (k_1, *, *, ..., *)$ , have  $k_1 = 0$ 

Then 
$$k_2\mathbf{r}_2 + k_3\mathbf{r}_3 = \mathbf{0}$$
. Since  $k_2\mathbf{r}_2 + k_3\mathbf{r}_3 = (0, 0, k_2, *, ..., *)$ , have  $k_2 = 0$ .

Then  $k_3\mathbf{r}_3 = \mathbf{0}$ . Since  $k_3\mathbf{r}_3 = (0, 0, 0, 0, 0, 0, k_3)$ , have  $k_3 = 0$ .

# Finding basis for the row space and the null space

In order to find a basis for the row space of a matrix A, do

- transform A (by elementary row operations) to row echelon form R;
- the rows  $\underline{\text{in } R}$  with the leading 1s form a basis for the row space of A.

Bonus: In order to find a basis for span(S) for a finite set S of vectors, do

• form a matrix whose row vectors are the vectors in S and then do as above.

From the last lecture, we know:

In order to find a basis for the null space of A, do

- find the general solution to the system  $A\mathbf{x} = \mathbf{0}$ ;
- for each free variable x, take the solution (vector  $\mathbf{v}_x$ ) in which x=1 and the other free variables are set to 0:
- these vectors  $\mathbf{v}_{x}$  together form a basis for the null space.

## Elementary row operations and the column space

Elementary row operations can change the column space: for example, let

$$A = \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix} \text{ and } B = \begin{pmatrix} 1 & 3 \\ 0 & 0 \end{pmatrix}.$$

B is obtained from A by an elementary row operation: adding  $(-2) \cdot r_1$  to  $r_2$ .

The column space of 
$$A$$
 is  $span(\begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 6 \end{pmatrix}) = \{k \cdot \begin{pmatrix} 1 \\ 2 \end{pmatrix} \mid k \in \mathbb{R}\}.$ 

The column space of 
$$B$$
 is  $span(\left(\begin{array}{c}1\\0\end{array}\right),\left(\begin{array}{c}3\\0\end{array}\right))=\{k\cdot\left(\begin{array}{c}1\\0\end{array}\right)\mid k\in\mathbb{R}\}.$ 

Clearly, these are different spaces.

Generally, how can we find a basis for the column space of a matrix?

# Elementary row operations and the column space

Elementary row operations do not change dependencies between column vectors of a matrix: if, for example,  $\mathbf{c}_2$ ,  $\mathbf{c}_3$ ,  $\mathbf{c}_5$ ,  $\mathbf{c}_7$  are column vectors of a matrix such that  $k_2\mathbf{c}_2 + k_3\mathbf{c}_3 + k_5\mathbf{c}_5 + k_7\mathbf{c}_7 = \mathbf{0}$  holds before an operation then it also holds after.

**Exercise:** Check this (the proof is easy).

### **Theorem**

Let B be a matrix obtained from matrix A by an elementary row operation.

- A subset S of column vectors in A is linearly independent iff the corresponding set of column vectors in B is such.
- A subset S of column vectors in A is a basis for the column space of A iff the corresponding set of column vectors in B is a basis for the column space of B.

### **Theorem**

If a matrix R is in row echelon form then the column vectors with the leading 1s form a basis for the column space of R.

Proofs of both theorems are straightforward, but a bit cumbersome - omitted.

# Finding basis for the column space

Column space of a matrix  $A = \text{row space of } A^T$ . They have the same bases.

To find a basis for the column space that is a subset of the columns :

- transform A (by elementary row operations) to row echelon form R;
- select all columns in R that have leading 1s;
- the corresponding columns in A form the required basis.

Example: columns 1, 3, and 5 form a basis of the column space of this matrix

Btw, how do we find a basis for the row space that is a subset of the rows?

## Rank of a matrix

#### **Theorem**

The row space and the column space of a matrix have the same dimension.

## Proof.

Dimension of each space is equal to the number of leading 1s in row echelon form of the matrix.  $\hfill\Box$ 

### **Definition**

The rank of a matrix A, denoted by rank(A), is the dimension of its row space.

## Properties of rank

### **Definition**

The rank of a matrix A, denoted by rank(A), is the dimension of its row space.

### Some properties of rank:

- $rank(A) = rank(A^T)$  because row space of A = column space of  $A^T$
- If A has size  $m \times n$  then  $rank(A) \le \min(m, n)$  this is because rank(A) is the dimension of a subspace in  $\mathbb{R}^m$  and of a subspace in  $\mathbb{R}^n$ .
- If A has size  $n \times n$ , then rank(A) = n iff  $det(A) \neq 0$  iff A is invertible because rank(A) = n means that the rows of A span (and form a basis in)  $\mathbb{R}^n$ .
- If A has size  $m \times n$  then rank(A) = 1 iff A = CR where C is an  $m \times 1$  matrix (i.e. a single column) and R is an  $1 \times n$  matrix (i.e a single row). This is a special case of rank decomposition (we might prove it later.)

How to compute rank(A)? Many ways.

One is to transform to row echelon form and count leading 1s. Additional trick: can use elementary column operations too (because  $rank(A) = rank(A^T)$ ).

# Rank and nullity

### **Definition**

The nullity of A, denoted by nullity(A), is the dimension of the null space of A.

### Lemma

For any  $m \times n$  matrix A, rank(A) and nullity(A) are the numbers of leading and free variables, respectively, in the general solution to  $A\mathbf{x} = \mathbf{0}$ .

## Theorem (Dimension Theorem for Matrices)

For any matrix A with n columns, rank(A) + nullity(A) = n.

### Proof.

The system  $A\mathbf{x} = \mathbf{0}$  has n variables. Now use the previous lemma.

To rephrase: rank(A) determines the dimension of the solution space of  $A\mathbf{x} = \mathbf{0}$ .

# Orthogonal complement

### **Definition**

If W is a subspace of  $\mathbb{R}^n$  then the orthogonal complement of W, denoted by  $W^{\perp}$ , is defined as

$$W^{\perp} = \{ \mathbf{v} \in V \mid \mathbf{v} \cdot \mathbf{w} = 0 \text{ for every } \mathbf{w} \in W \}.$$

### Lemma

If W is a subspace of  $\mathbb{R}^n$  then

- $W^{\perp}$  is a subspace of  $\mathbb{R}^n$ ;
- **2**  $W \cap W^{\perp} = \{\mathbf{0}\};$
- **3**  $(W^{\perp})^{\perp} = W$ .

### **Theorem**

If A is an  $m \times n$  matrix then the null space of A and the row space of A are orthogonal complements in  $\mathbb{R}^n$ .

**Exercise:** Prove the above lemma and theorem (all proofs are one-line).

## An application of rank in CS: low-rank approximation

- Fact: data is often stored in matrix form.
- Popular idea: approximate a matrix by a matrix of a low rank.
- Intuitively, rank measures complexity of a matrix. The low rank constraint is related to a constraint on the complexity of a model that fits the data. Go from high-complexity data to a low-rank model to make computation feasible.
- Some CS applications of low-rank approximation:
  - Data compression (via SVD singular value decomposition for matrices)
  - Machine learning
  - Recommender systems
  - Natural language processing

## What we learnt today

• The four fundamental spaces of an  $m \times n$  matrix A:

subspaces of $\mathbb{R}^n$	subspaces of $\mathbb{R}^m$
row space of A	column space of A
null space of $A$	null space of $A^T$

The subspaces in each column are orthogonal complements of each other.

- How to find bases of these spaces
- Rank and nullity of a matrix, and how they are related

#### Next time:

• Matrix transformations from  $\mathbb{R}^n$  to  $\mathbb{R}^m$