

# SI231b: Matrix Computations

## Lecture 3: Basic Concepts (Part 2)

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- ▶ subspaces, span
- ▶ linear independence, basis
- ▶ range and null spaces
- ▶ dimension of subspaces, rank
- ▶ inner product, orthogonality
- ▶ matrix products, computational complexity

Obvious interpretation of subspaces in the visual spaces  $\mathbb{R}^2$  and  $\mathbb{R}^3$

- ▶ flat surfaces passing through the origin

## Spanning sets

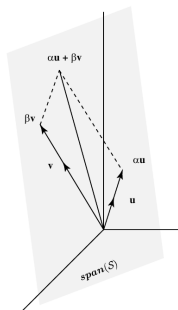
- ▶ for a set of vectors  $\mathcal{S} = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_r\}$ , the subspaces

$$\text{span}(\mathcal{S}) = \{\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_r \mathbf{v}_r\}$$

generated by forming all linear combinations of vectors from  $\mathcal{S}$  is called the space spanned by  $\mathcal{S}$

- ▶ If  $\mathcal{V}$  is a vector space such that  $\mathcal{V} = \text{span}(\mathcal{S})$ , we say  $\mathcal{S}$  is a spanning set for  $\mathcal{V}$ .

# Subspaces



►  $S = \{\mathbf{u}, \mathbf{v}\}$  is a spanning set of the indicated plan in the left figure

► The unit vectors

$$\left\{ \mathbf{e}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \mathbf{e}_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \mathbf{e}_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \right\}$$

spans  $\mathbb{R}^3$

If  $\mathcal{X}$  and  $\mathcal{Y}$  are subspaces of a vector space  $\mathcal{V}$ ,

- $\mathcal{X} \cap \mathcal{Y}$  is also a subspace
- $\mathcal{X} \cup \mathcal{Y}$  need not be a subspace

If  $\mathcal{X}$  and  $\mathcal{Y}$  are subspaces of a vector space  $\mathcal{V}$ , define the sum of two subspaces by

$$\mathcal{X} + \mathcal{Y} = \{\mathbf{x} + \mathbf{y} | \mathbf{x} \in \mathcal{X} \text{ and } \mathbf{y} \in \mathcal{Y}\}$$

then

- ▶ the sum  $\mathcal{X} + \mathcal{Y}$  is again a subspace of  $\mathcal{V}$
- ▶ if  $\mathcal{S}_X, \mathcal{S}_Y$  spans  $\mathcal{X}$  and  $\mathcal{Y}$ , then  $\mathcal{S}_X \cup \mathcal{S}_Y$  spans  $\mathcal{X} + \mathcal{Y}$

## Examples

- ▶ If  $\mathcal{X} \subset \mathbb{R}^2$  and  $\mathcal{Y} \subset \mathbb{R}^2$  are subspaces defined by two different lines through the origin, then  $\mathcal{X} + \mathcal{Y} = \mathbb{R}^2$
- ▶ If  $\mathcal{X}$  is a subspace represents a plane passing through the origin in  $\mathbb{R}^3$  and  $\mathcal{Y}$  is a subspace defined by the line through the origin that is perpendicular to  $\mathcal{X}$ ,  $\mathcal{X} + \mathcal{Y} = \mathbb{R}^3$

# Subspaces and Linear Independence

**Question:** any span is a subspace, can any subspace be written as a span?

## 定理

Let  $\mathcal{S}$  be a subspace of  $\mathbb{R}^m$ . There exists a positive integer  $n$  and a collection of vectors  $\mathbf{a}_1, \dots, \mathbf{a}_n \in \mathcal{S}$  such that  $\mathcal{S} = \text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ .

► **Implication:** we can always represent a subspace by a span

## Linear Independence

A collection of vectors  $\mathbf{a}_1, \dots, \mathbf{a}_n \in \mathbb{R}^m$  is said to be **linearly independent** if

$$\sum_{i=1}^n \alpha_i \mathbf{a}_i \neq \mathbf{0}, \quad \text{for all } \alpha \in \mathbb{R}^n \text{ with } \alpha \neq \mathbf{0};$$

► an equivalent way of defining linear dependence:  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$  is a linearly dependent vector set if there exists  $\alpha \in \mathbb{R}^m$ ,  $\alpha \neq \mathbf{0}$ , such that

$$\sum_{i=1}^n \alpha_i \mathbf{a}_i = \mathbf{0}.$$

Some known facts:

- ▶ if  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$  is linearly independent, then any  $\mathbf{a}_j$  *cannot* be a linear combination of the other  $\mathbf{a}_i$ 's; i.e.,  $\mathbf{a}_j \neq \sum_{i \neq j} \alpha_i \mathbf{a}_i$  for any  $\alpha_i$ 's.
- ▶ if  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$  is linearly dependent, then *there exists* an  $\mathbf{a}_j$  such that  $\mathbf{a}_j$  is a linear combination of the other  $\mathbf{a}_i$ 's; i.e.,  $\mathbf{a}_j = \sum_{i \neq j} \alpha_i \mathbf{a}_i$  for some  $\alpha_i$ 's.
- ▶ if  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$  is linearly independent, then  $n \leq m$  must hold.
- ▶ let  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$  be a linearly independent vector set. Suppose  $\mathbf{y} \in \text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ . Then the coefficient  $\alpha$  for the representation

$$\mathbf{y} = \sum_{i=1}^n \alpha_i \mathbf{a}_i$$

is unique; i.e., there does *not* exist a  $\beta \in \mathbb{R}^n$ ,  $\beta \neq \alpha$ , such that

$$\mathbf{y} = \sum_{i=1}^n \beta_i \mathbf{a}_i.$$

Let  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\} \subset \mathbb{R}^m$ , and denote  $\{i_1, \dots, i_k\} \subseteq \{1, \dots, n\}$  as an index subset with  $k \leq n$  and  $i_j \neq i_l$  for all  $j \neq l$ .

A vector subset  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is called a **maximal linear independent** subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$  if

1.  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is linear independent;
  2.  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is not contained by any other linearly independent subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ .
- physical meaning: find a set of non-redundant vectors from  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$



► Example:

$$\mathbf{a}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{a}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{a}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \quad \mathbf{a}_4 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}.$$

The linear independent subsets of  $\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{a}_4\}$  are

$$\begin{aligned} &\{\mathbf{a}_1\}, \{\mathbf{a}_2\}, \{\mathbf{a}_3\}, \{\mathbf{a}_4\}, \\ &\{\mathbf{a}_1, \mathbf{a}_2\}, \{\mathbf{a}_1, \mathbf{a}_3\}, \{\mathbf{a}_1, \mathbf{a}_4\}, \{\mathbf{a}_2, \mathbf{a}_3\}, \{\mathbf{a}_2, \mathbf{a}_4\}, \{\mathbf{a}_3, \mathbf{a}_4\}, \\ &\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}, \quad \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_4\}, \quad \{\mathbf{a}_1, \mathbf{a}_3, \mathbf{a}_4\}. \end{aligned}$$

But the maximal linear independent subsets are

$$\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}, \quad \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_4\}, \quad \{\mathbf{a}_1, \mathbf{a}_3, \mathbf{a}_4\}.$$

Facts:

- ▶  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is a maximal linear independent subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ 
  - if and only if  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}, \mathbf{a}_j\}$  is linear dependent for any  $j \in \{1, \dots, n\} \setminus \{i_1, \dots, i_k\}$
- ▶ if  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is a maximal linearly independent subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ , then

$$\text{span}\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\} = \text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\}.$$

- ▶ key concepts for defining the basis of a subspace

Let  $\mathcal{S} \subseteq \mathbb{R}^m$  be a nontrivial subspace. A vector set  $\{\mathbf{b}_1, \dots, \mathbf{b}_k\} \subset \mathbb{R}^m$  is called a **basis** for  $\mathcal{S}$  if  $\{\mathbf{b}_1, \dots, \mathbf{b}_k\}$  is linearly independent and

$$\mathcal{S} = \text{span}\{\mathbf{b}_1, \dots, \mathbf{b}_k\}.$$

► Examples:

let  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  be a maximal linearly independent vector subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ . Then,  $\{\mathbf{a}_{i_1}, \dots, \mathbf{a}_{i_k}\}$  is a basis for  $\text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ .

Some facts:

- we may have more than one basis for  $\mathcal{S}$
- all bases for  $\mathcal{S}$  have the same number of elements; i.e., if  $\{\mathbf{b}_1, \dots, \mathbf{b}_k\}$  and  $\{\mathbf{c}_1, \dots, \mathbf{c}_l\}$  are bases for  $\mathcal{S}$ , then  $k = l$

## Range Spaces

1. The range of a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$  denoted by  $\mathcal{R}(\mathbf{A})$ , is defined to be the subspace of  $\mathbb{R}^m$  generated by the range of  $\mathbf{A}\mathbf{x}$

$$\mathcal{R}(\mathbf{A}) = \{\mathbf{y} \in \mathbb{R}^m \mid \mathbf{y} = \mathbf{A}\mathbf{x}, \mathbf{x} \in \mathbb{R}^n\} \subset \mathbb{R}^m$$

- also called **column space**

2. The range of  $\mathbf{A}^T$  is the subspace of  $\mathbb{R}^n$  defined by

$$\mathcal{R}(\mathbf{A}^T) = \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{x} = \mathbf{A}^T\mathbf{y}, \mathbf{y} \in \mathbb{R}^m\} \subset \mathbb{R}^n$$

- also called **row space**

3.  $\mathcal{R}(\mathbf{A})$  is the set of all “images” of vectors  $\mathbf{x} \in \mathbb{R}^n$  under transformation by  $\mathbf{A}$ , sometimes  $\mathcal{R}(\mathbf{A})$  is called the image space of  $\mathbf{A}$ .

## Null Spaces

1. The null space of a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$  denoted by  $\mathcal{N}(\mathbf{A})$ , is defined to be the subspace of  $\mathbb{R}^n$  with

$$\mathcal{N}(\mathbf{A}) = \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{A}\mathbf{x} = \mathbf{0}\} \subset \mathbb{R}^n$$

- $\mathcal{N}(\mathbf{A})$  is simply the set of all solutions to the homogeneous system  $\mathbf{A}\mathbf{x} = \mathbf{0}$ .

2. Similarly, the nullspace of  $\mathbf{A}^T$ , i.e.,  $\mathcal{N}(\mathbf{A}^T)$

$$\mathcal{N}(\mathbf{A}^T) = \{\mathbf{y} \in \mathbb{R}^m \mid \mathbf{A}^T\mathbf{y} = \mathbf{0}\} \subset \mathbb{R}^m$$

- also called **left-hand nullspace** of  $\mathbf{A}$  since it is the set of all solutions to the left-hand homogeneous system  $\mathbf{y}^T\mathbf{A} = \mathbf{0}^T$

The **dimension** of a nontrivial subspace  $\mathcal{S}$  is defined as the **number of elements of a basis for  $\mathcal{S}$** .

- ▶ the dimension of the trivial subspace  $\{0\}$  is defined as 0.
- ▶  $\dim \mathcal{S}$  will be used as the notation for denoting the dimension of  $\mathcal{S}$
- ▶ physical meaning: effective degrees of freedom of the subspace
- ▶ examples:
  - $\dim \mathbb{R}^m = m$
  - if  $k$  is the number of maximal linearly independent vectors of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ , then  $\dim \text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\} = k$ .

## Properties:

- ▶ let  $\mathcal{S}_1, \mathcal{S}_2 \subseteq \mathbb{R}^m$  be subspaces. If  $\mathcal{S}_1 \subseteq \mathcal{S}_2$ , then  $\dim \mathcal{S}_1 \leq \dim \mathcal{S}_2$ .
- ▶ let  $\mathcal{S}_1, \mathcal{S}_2 \subseteq \mathbb{R}^m$  be subspaces. If  $\mathcal{S}_1 \subseteq \mathcal{S}_2$  and  $\dim \mathcal{S}_1 = \dim \mathcal{S}_2$ , then  $\mathcal{S}_1 = \mathcal{S}_2$ .
- ▶ let  $\mathcal{S} \subseteq \mathbb{R}^m$  be a subspace. Then

$$\dim \mathcal{S} = m \iff \mathcal{S} = \mathbb{R}^m.$$

- ▶ let  $\mathcal{S}_1, \mathcal{S}_2 \subseteq \mathbb{R}^m$  be subspaces. We have  $\dim(\mathcal{S}_1 + \mathcal{S}_2) \leq \dim \mathcal{S}_1 + \dim \mathcal{S}_2$ .
  - as a more advanced result, we also have

$$\dim(\mathcal{S}_1 + \mathcal{S}_2) = \dim \mathcal{S}_1 + \dim \mathcal{S}_2 - \dim(\mathcal{S}_1 \cap \mathcal{S}_2).$$

The **rank** of a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , denoted by  $\text{rank}(\mathbf{A})$ , is defined as the number of elements of a maximal linearly independent subset of  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ .

- ▶  $\text{rank}(\mathbf{A})$  is the maximum number of linearly independent columns of  $\mathbf{A}$
- ▶  $\dim \mathcal{R}(\mathbf{A}) = \text{rank}(\mathbf{A})$  by definition

Facts:

- ▶  $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^T)$ , i.e., the rank of  $\mathbf{A}$  is also the maximum number of linearly independent rows of  $\mathbf{A}$
- ▶  $\text{rank}(\mathbf{A} + \mathbf{B}) \leq \text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B})$
- ▶  $\text{rank}(\mathbf{AB}) \leq \min\{\text{rank}(\mathbf{A}), \text{rank}(\mathbf{B})\}$ .
  - Equality holds when  $\mathbf{A}$  and  $\mathbf{B}$  are full rank.



- ▶  $\mathbf{A} \in \mathbb{R}^{m \times n}$  is said to have
  - **full column rank** if the columns of  $\mathbf{A}$  are linearly independent (more precisely, the collection of *all* columns of  $\mathbf{A}$  is linearly independent)
    - ▶  $\mathbf{A} \in \mathbb{R}^{m \times n}$  being of full column rank  $\iff m \geq n, \text{rank}(\mathbf{A}) = n$
  - **full row rank** if the rows of  $\mathbf{A}$  are linearly independent
    - ▶  $\mathbf{A} \in \mathbb{R}^{m \times n}$  being of full row rank  $\iff m \leq n, \text{rank}(\mathbf{A}) = m$
  - **full rank** if  $\text{rank}(\mathbf{A}) = \min\{m, n\}$ ; i.e., it has either full column rank or full row rank
  - **rank deficient** if  $\text{rank}(\mathbf{A}) < \min\{m, n\}$

A **square** matrix  $\mathbf{A}$  is said to be **nonsingular** or **invertible** if

- ▶  $\mathbf{A}$  is full rank
- ▶ all the columns of  $\mathbf{A}$  are linear independent
- ▶  $\mathbf{Ax} = \mathbf{0} \iff \mathbf{x} = \mathbf{0}$
- ▶ alternatively, we say  $\mathbf{A}$  is singular if  $\mathbf{Ax} = \mathbf{0}$  for some  $\mathbf{x} \neq \mathbf{0}$ .

The **inverse** of an invertible  $\mathbf{A}$ , denoted by  $\mathbf{A}^{-1}$ , is a square matrix that satisfies

$$\mathbf{A}^{-1}\mathbf{A} = \mathbf{I}.$$

Facts (for a nonsingular  $\mathbf{A}$ ):

- ▶  $\mathbf{A}^{-1}$  always exists and is unique (or there are no two inverses of  $\mathbf{A}$ )
- ▶  $\mathbf{A}^{-1}$  is nonsingular
- ▶  $\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$
- ▶  $(\mathbf{A}^{-1})^{-1} = \mathbf{A}$
- ▶  $(\mathbf{A}\mathbf{B})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$ , where  $\mathbf{A}, \mathbf{B}$  are square and nonsingular
- ▶  $(\mathbf{A}^T)^{-1} = (\mathbf{A}^{-1})^T$ 
  - as a shorthand notation, we will denote  $\mathbf{A}^{-T} = (\mathbf{A}^T)^{-1}$

The **inner product** of two vectors  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$  is defined as

$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n y_i x_i = \mathbf{y}^T \mathbf{x}.$$

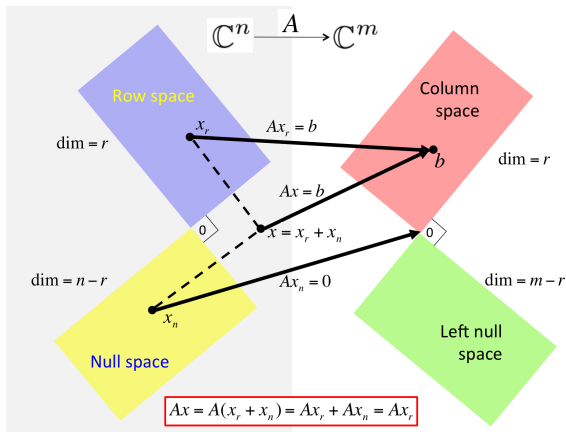
- ▶  $\mathbf{x}, \mathbf{y}$  are said to be **orthogonal** to each other if  $\langle \mathbf{x}, \mathbf{y} \rangle = 0$
- ▶  $\mathbf{x}, \mathbf{y}$  are said to be **parallel** if  $\mathbf{x} = \alpha \mathbf{y}$  for some  $\alpha$

The **angle** between two vectors  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$  is defined as

$$\theta = \arccos \left( \frac{\mathbf{y}^T \mathbf{x}}{\|\mathbf{x}\|_2 \|\mathbf{y}\|_2} \right).$$

- ▶  $\mathbf{x}, \mathbf{y}$  are orthogonal if  $\theta = \pi/2$
- ▶  $\mathbf{x}, \mathbf{y}$  are parallel if  $\theta = 0$  or  $\theta = \pi$

# Orthogonality of Four Fundamental Subspaces



- $\mathcal{R}(A) \perp \mathcal{N}(A^T)$
- $\mathcal{R}(A^T) \perp \mathcal{N}(A)$
- Details will follow in the later part

## Cauchy-Schwartz inequality:

$$|\mathbf{x}^T \mathbf{y}| \leq \|\mathbf{x}\|_2 \|\mathbf{y}\|_2.$$

Also, the above equality holds if and only if  $\mathbf{x} = \alpha \mathbf{y}$  for some  $\alpha \in \mathbb{R}$ .

► Proof: suppose  $\mathbf{y} \neq \mathbf{0}$ ; the case of  $\mathbf{y} = \mathbf{0}$  is trivial. For any  $\alpha \in \mathbb{R}$ ,

$$0 \leq \|\mathbf{x} - \alpha \mathbf{y}\|_2^2 = (\mathbf{x} - \alpha \mathbf{y})^T (\mathbf{x} - \alpha \mathbf{y}) = \|\mathbf{x}\|_2^2 - 2\alpha \mathbf{x}^T \mathbf{y} + \alpha^2 \|\mathbf{y}\|_2^2. \quad (*)$$

Also, the equality above holds if and only if  $\mathbf{x} = \beta \mathbf{y}$  for some  $\beta$ . Let

$$f(\alpha) = \|\mathbf{x}\|_2^2 - 2\alpha \mathbf{x}^T \mathbf{y} + \alpha^2 \|\mathbf{y}\|_2^2.$$

The function  $f$  is minimized when  $\alpha = (\mathbf{x}^T \mathbf{y}) / \|\mathbf{y}\|_2^2$ . Plugging this  $\alpha$  back to  $(*)$  leads to the desired result.

## Hölder inequality:

$$|\mathbf{x}^T \mathbf{y}| \leq \|\mathbf{x}\|_p \|\mathbf{y}\|_q,$$

for any  $p, q$  such that  $1/p + 1/q = 1$ ,  $p \geq 1$ .

### ► examples:

- $(p, q) = (2, 2)$ : Cauchy-Schwartz inequality
- $(p, q) = (1, \infty)$ :  $|\mathbf{x}^T \mathbf{y}| \leq \|\mathbf{x}\|_1 \|\mathbf{y}\|_\infty$ .

This can be easily verified to be true:

$$|\mathbf{x}^T \mathbf{y}| \leq \sum_{i=1}^n |x_i y_i| \leq \max_j |y_j| \left( \sum_{i=1}^n |x_i| \right) = \|\mathbf{x}\|_1 \|\mathbf{y}\|_\infty.$$

# Matrix Product Representations

Let  $\mathbf{A} \in \mathbb{R}^{m \times k}$ ,  $\mathbf{B} \in \mathbb{R}^{k \times n}$ , and consider

$$\mathbf{C} = \mathbf{AB}.$$

► column representation:

$$\mathbf{c}_i = \mathbf{A}\mathbf{b}_i, \quad i = 1, \dots, n$$

► inner-product representation: redefine  $\mathbf{a}_i \in \mathbb{R}^k$  as the  $i$ th row of  $\mathbf{A}$ .

$$\mathbf{AB} = \begin{bmatrix} \mathbf{a}_1^T \\ \vdots \\ \mathbf{a}_m^T \end{bmatrix} \begin{bmatrix} \mathbf{b}_1 & \cdots & \mathbf{b}_n \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1^T \mathbf{b}_1 & \cdots & \mathbf{a}_1^T \mathbf{b}_n \\ \vdots & & \vdots \\ \mathbf{a}_m^T \mathbf{b}_1 & \cdots & \mathbf{a}_m^T \mathbf{b}_n \end{bmatrix}$$

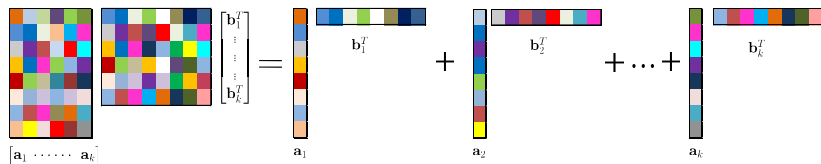
Thus,

$$c_{ij} = \mathbf{a}_i^T \mathbf{b}_j, \quad \text{for any } i, j.$$



- **outer-product representation:** redefine  $\mathbf{b}_i \in \mathbb{R}^k$  as the  $i$ th row of  $\mathbf{B}$ . Thus,

$$\mathbf{C} = \mathbf{AB} = \sum_{i=1}^k \mathbf{a}_i \mathbf{b}_i^T$$



- ▶ The matrix of the form  $\mathbf{X} = \mathbf{a}\mathbf{b}^T$  for some  $\mathbf{a}, \mathbf{b}$  is called a **rank-one outer product**.
  - It can be verified that  $\text{rank}(\mathbf{X}) \leq 1$ , and  $\text{rank}(\mathbf{X}) = 1$  if  $\mathbf{a} \neq \mathbf{0}, \mathbf{b} \neq \mathbf{0}$ .
- ▶ the outer-product representation

$$\mathbf{C} = \sum_{i=1}^k \mathbf{a}_i \mathbf{b}_i^T$$

is a sum of  $k$  rank-one outer products.

- ▶ does it mean that  $\text{rank}(\mathbf{C}) = k$ ?
  - $\text{rank}(\mathbf{C}) \leq \sum_{i=1}^k \text{rank}(\mathbf{a}_i \mathbf{b}_i^T) \leq k$  is true <sup>1</sup>
  - but the above equality is generally not attained; e.g.,  $k = 2$ ,  $\mathbf{a}_1 = \mathbf{a}_2$ ,  $\mathbf{b}_1 = -\mathbf{b}_2$  leads to  $\mathbf{C} = \mathbf{0}$
  - $\text{rank}(\mathbf{C}) = k$  only when  $\mathbf{A}$  and  $\mathbf{B}$  are full rank (**take home exam**)

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<sup>1</sup>use the rank inequality  $\text{rank}(\mathbf{A} + \mathbf{B}) \leq \text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B})$ .

Sometimes it may be useful to manipulate matrices in a block form.

- ▶ let  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{x} \in \mathbb{R}^n$ . By partitioning

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$$

where  $\mathbf{A}_1 \in \mathbb{R}^{m \times n_1}$ ,  $\mathbf{A}_2 \in \mathbb{R}^{m \times n_2}$ ,  $\mathbf{x}_1 \in \mathbb{R}^{n_1}$ ,  $\mathbf{x}_2 \in \mathbb{R}^{n_2}$ , with  $n_1 + n_2 = n$ , we can write

$$\mathbf{Ax} = \mathbf{A}_1\mathbf{x}_1 + \mathbf{A}_2\mathbf{x}_2$$

- ▶ similarly, by partitioning

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix},$$

we can write

$$\mathbf{Ax} = \begin{bmatrix} \mathbf{A}_{11}\mathbf{x}_1 + \mathbf{A}_{12}\mathbf{x}_2 \\ \mathbf{A}_{21}\mathbf{x}_1 + \mathbf{A}_{22}\mathbf{x}_2 \end{bmatrix}$$

- ▶ consider  $\mathbf{AB}$ . By an appropriate partitioning,

$$\mathbf{AB} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 \end{bmatrix} \begin{bmatrix} \mathbf{B}_1 \\ \mathbf{B}_2 \end{bmatrix} = \mathbf{A}_1\mathbf{B}_1 + \mathbf{A}_2\mathbf{B}_2$$

- ▶ similarly, by an appropriate partitioning,

$$\mathbf{AB} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \end{bmatrix} \begin{bmatrix} \mathbf{B}_1 & \mathbf{B}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{A}_1\mathbf{B}_1 & \mathbf{A}_1\mathbf{B}_2 \\ \mathbf{A}_2\mathbf{B}_1 & \mathbf{A}_2\mathbf{B}_2 \end{bmatrix}$$

- ▶ we showcase two-block partitioning only, but the same manipulations apply to multi-block partitioning like

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \cdots & \mathbf{A}_{1q} \\ \vdots & & \vdots \\ \mathbf{A}_{p1} & \cdots & \mathbf{A}_{pq} \end{bmatrix}$$

- ▶ all the concepts described above apply to the complex case
- ▶ we only need to replace every “ $\mathbb{R}$ ” with “ $\mathbb{C}$ ”, and every “ $T$ ” with “ $H$ ”; e.g.,

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$$\text{span}\{\mathbf{a}_1, \dots, \mathbf{a}_n\} = \{\mathbf{y} \in \mathbb{C}^m \mid \mathbf{y} = \sum_{i=1}^n \alpha_i \mathbf{a}_i, \alpha \in \mathbb{C}^n\},$$

- $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{y}^H \mathbf{x};$
- $\|\mathbf{x}\|_2 = \sqrt{\mathbf{x}^H \mathbf{x}},$  and so forth.

► the concepts also apply to the matrix case

- e.g., we may write

$$\text{span}\{\mathbf{A}_1, \dots, \mathbf{A}_k\} = \{\mathbf{Y} \in \mathbb{R}^{m \times n} \mid \mathbf{Y} = \sum_{i=1}^k \alpha_i \mathbf{A}_i, \alpha \in \mathbb{R}^k\}.$$

- sometimes it is more convenient to *vectorize*  $\mathbf{X}$  as a vector  $\mathbf{x} \in \mathbb{R}^{mn}$ , and use the same treatment as in the  $\mathbb{R}^n$  case
- inner product for  $\mathbb{R}^{m \times n}$ :

$$\langle \mathbf{X}, \mathbf{Y} \rangle = \sum_{i=1}^m \sum_{j=1}^n x_{ij} y_{ij} = \text{tr}(\mathbf{Y}^T \mathbf{X}),$$

- the matrix version of the Euclidean norm is called the **Frobenius norm**:

$$\|\mathbf{X}\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |x_{ij}|^2} = \sqrt{\text{tr}(\mathbf{X}^T \mathbf{X})}$$

► extension to  $\mathbb{C}^{m \times n}$  is just as straightforward as in that to  $\mathbb{C}^n$

- ▶ every vector/matrix operation such as  $\mathbf{x} + \mathbf{y}$ ,  $\mathbf{y}^T \mathbf{x}$ ,  $\mathbf{A}\mathbf{x}$ , ... incurs computational costs, and they cost more as the vector and matrix sizes get bigger
- ▶ we typically look at floating point arithmetic operations, such as add, subtract, multiply, and divide

- ▶ **flops:** one flop means one floating point arithmetic operation.
- ▶ flops count of some standard vector/matrix operations:  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ ,  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{B} \in \mathbb{R}^{n \times p}$ ,
  - $\mathbf{x} + \mathbf{y}$ :  $n$  adds, so  $n$  flops
  - $\mathbf{y}^T \mathbf{x}$ :  $n$  multiplies and  $n - 1$  adds, so  $2n - 1$  flops
  - $\mathbf{Ax}$ :  $m$  inner products, so  $m(2n - 1)$  flops
  - $\mathbf{AB}$ : do “ $\mathbf{Ax}$ ” above  $p$  times, so  $pm(2n - 1)$  flops



- ▶ we are often interested in the *order* of the complexity
- ▶ **big  $\mathcal{O}$  notation:** given two functions  $f(n), g(n)$ , the notation

$$f(n) = \mathcal{O}(g(n))$$

means that there exists a constant  $C > 0$  and  $n_0$  such that  $|f(n)| \leq C|g(n)|$  for all  $n \geq n_0$ .

- ▶ big  $\mathcal{O}$  complexities of standard vector/matrix operations:
  - $\mathbf{x} + \mathbf{y}$ :  $\mathcal{O}(n)$  flops
  - $\mathbf{y}^T \mathbf{x}$ :  $\mathcal{O}(n)$  flops
  - $\mathbf{Ax}$ :  $\mathcal{O}(mn)$  flops
  - $\mathbf{AB}$ :  $\mathcal{O}(mnp)$  flops

- ▶ **Discussion:** flop counts do not always translate into the actual efficiency of the execution of an algorithm
- ▶ things like pipelining, FPGA, parallel computing (multiple GPUs, multiple servers, cloud computing), etc., can make the story different.
- ▶ flop counts also ignore memory usage and other overheads...
- ▶ that said, we need at least a crude measure of the computational cost of an algorithm, and counting the flops serves that purpose.

# How to Save Computations

- ▶ computational complexities depend much on how we design and write an algorithm
- ▶ generally, it is about
  - top-down, analysis-guided, designs:
    - ▶ seen in class, research papers
    - ▶ looks elegant
- ▶ facts are
  - usually *not* taught much in class
  - not commonplace in papers
  - subtly depends on your problem at hand
  - a bunch of small differences can make a big difference, say in actual running time
- ▶ here we give several, but by no means all, tips for saving computations

# How to Save Computations

- ▶ apply matrix operations wisely
- ▶ Example: try this on Matlab

```
>> A=randn(5000,2);  
>> B=randn(2,10000);  
>> C=randn(10000,10000);  
>>  
>> tic; D= A*B*C; toc  
Elapsed time is 1.334183 seconds.  
>> tic; D= (A*B)*C; toc      % ask Matlab to do AB first  
Elapsed time is 1.205725 seconds.  
>> tic; D= A*(B*C); toc      % ask Matlab to do BC first  
Elapsed time is 0.067979 seconds.
```

► let us analyze the complexities in the last example

- $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{B} \in \mathbb{R}^{n \times p}$ ,  $\mathbf{C} \in \mathbb{R}^{p \times p}$ , with  $n \ll \min\{m, p\}$ .

- We want to compute  $\mathbf{D} = \mathbf{ABC}$ .

- if we compute  $\mathbf{AB}$  first, and then  $\mathbf{D} = (\mathbf{AB})\mathbf{C}$ , the flop count will be

$$\mathcal{O}(mnp) + \mathcal{O}(mp^2) = \mathcal{O}(m(n+p)p) \approx \mathcal{O}(mp^2)$$

- if we compute  $\mathbf{BC}$  first, and then  $\mathbf{D} = \mathbf{A}(\mathbf{BC})$ , the flop count will be

$$\mathcal{O}(np^2) + \mathcal{O}(mnp) = \mathcal{O}((m+p)np).$$

- the 2nd option is preferable if  $n$  is much smaller than  $m, p$

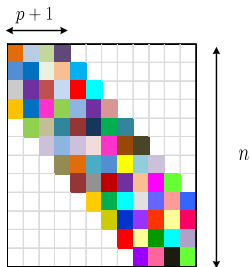
# How to Save Computations

- ▶ use **structures**, if available
- ▶ example: let  $\mathbf{A} \in \mathbb{R}^{n \times n}$  and suppose that

$$a_{ij} = 0 \text{ for all } i, j \text{ such that } |i - j| > p,$$

for some integer  $p > 0$ .

- such a structured  $\mathbf{A}$  is called **banded matrix**
- if we don't use structures, computing  $\mathbf{A}\mathbf{x}$  requires  $\mathcal{O}(n^2)$
- if we use the banded + sparsity<sup>1</sup> structures, we can compute  $\mathbf{A}\mathbf{x}$  with  $\mathcal{O}(pn)$
- different problems may have different fancy/advanced structures to be exploited



<sup>1</sup>a vector or matrix is said to be sparse if it contains many zeros

## Readings for lecture 2 and 3

- ▶ Carl D. Meyer. *Matrix Analysis and Applied Linear Algebra*, SIAM, 2005.

Chapter 3.1 – 3.7, 4.1 – 4.5, 5.1 – 5.4

- ▶ Gene H. Golub and Charles F. Van Loan. *Matrix Computations*, Johns Hopkins University Press, 2013.

Chapter 1, 2.1 – 2.3