

LINEAR MAPPINGS [1.8]

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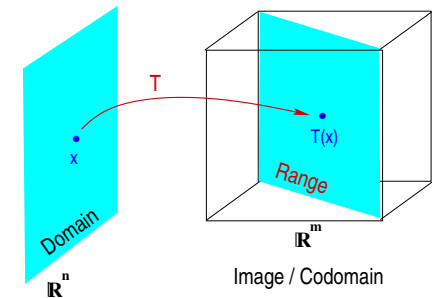
Introduction to linear mappings [1.8]

➤ A transformation or function or mapping from \mathbb{R}^n to \mathbb{R}^m is a rule which assigns to every x in \mathbb{R}^n a vector $T(x)$ in \mathbb{R}^m .

➤ \mathbb{R}^n is called the domain space of T and \mathbb{R}^m the image space or co-domain of T .

➤ Notation:

$$T : \mathbb{R}^n \longrightarrow \mathbb{R}^m$$



➤ $T(x)$ is the image of x under T

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Text:1.8-9 – Mappings

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Example: Take the mapping from \mathbb{R}^2 to \mathbb{R}^3 :

$$T : \mathbb{R}^2 \longrightarrow \mathbb{R}^3$$

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \longrightarrow T(x) = \begin{pmatrix} x_1 + x_2 \\ x_1 x_2 \\ x_1^2 + x_2^2 \end{pmatrix}$$

Example: Another mapping from \mathbb{R}^2 to \mathbb{R}^3 :

$$T : \mathbb{R}^2 \longrightarrow \mathbb{R}^3$$

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \longrightarrow T(x) = \begin{pmatrix} x_1 + x_2 \\ x_1 - x_2 \\ x_1 + 5x_2 \end{pmatrix}$$

What is the main difference between these 2 examples?

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Text:1.8-9 – Mappings

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Definition A mapping T is linear if:

- (i) $T(u + v) = T(u) + T(v)$ for u, v in the domain of T
- (ii) $T(\alpha u) = \alpha T(u)$ for all $\alpha \in \mathbb{R}$, all u in the domain of T

➤ The mapping of the second example given above is linear - but not for the first one.

➤ If a mapping is linear then $T(0) = 0$. (Why?)

Observation: A mapping is linear if and only if

$$T(\alpha u + \beta v) = \alpha T(u) + \beta T(v)$$

for all scalars α, β and all u, v in the domain of T .

Prove this

➤ Consequence:

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$$T(\alpha_1 u_1 + \alpha_2 u_2 + \cdots + \alpha_p u_p) = \alpha_1 T(u_1) + \alpha_2 T(u_2) + \cdots + \alpha_p T(u_p)$$

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Text:1.8-9 – Mappings

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➤ Given an $m \times n$ matrix A , consider the special mapping:

$$\begin{aligned} T : \mathbb{R}^n &\longrightarrow \mathbb{R}^m \\ x &\longrightarrow y = Ax \end{aligned}$$

🔍 Domain == ??; Image space == ??

➤ From what we saw earlier ['Properties of the matrix-vector product'] such mappings are linear

➤ As it turns out:

If T is linear, there exists a matrix A such that $T(x) = Ax$ for all x in \mathbb{R}^n

➤ In plain English: 'A linear mapping can be represented by a matvec'

➤ A is the representation of T .

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Text:1.8-9 – Mappings

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➤ How can we determine A ?

➤ Notation let

$$e_j = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad j\text{-th row} \quad x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_j \\ \vdots \\ \alpha_n \end{bmatrix}$$

- Write a vector x in \mathbb{R}^n as $x = \alpha_1 e_1 + \cdots + \alpha_n e_n$.
- Then note that $T(x) = \alpha_1 T(e_1) + \cdots + \alpha_n T(e_n)$
- Therefore the columns of the matrix representation of T must be the vectors $T(e_j)$ for $j = 1, \dots, n$

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Text:1.8-9 – Mappings

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🔍 Let A be a square matrix. Is the mapping $x \rightarrow x + Ax$ linear? If so find the matrix associated with it.

🔍 Same questions for the mapping $x \rightarrow Ax + \alpha x$ - where α is a scalar.

🔍 Express the following mapping from \mathbb{R}^3 to \mathbb{R}^2 in matrix/vector form:

$$\left| \begin{array}{l} y_1 = 2x_1 - x_2 + 1 \\ y_2 = x_2 - x_3 - 2 \end{array} \right.$$

➤ Is this a **linear** mapping?

🔍 Read Section 1.9 and explore the notions of **onto** mappings ('surjective') and **one-to-one** mappings ('injective') in the text. You must at least know the definitions.

🔍 A mapping is onto if and only if

🔍 A mapping is one-to-one if and only if

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Text:1.8-9 – Mappings

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Onto and one-to-one mappings

➤ Let T a mapping – not necessarily linear for now – from a domain set \mathcal{D} (subset of \mathbb{R}^n) into an image set \mathcal{I} (subset of \mathbb{R}^m)

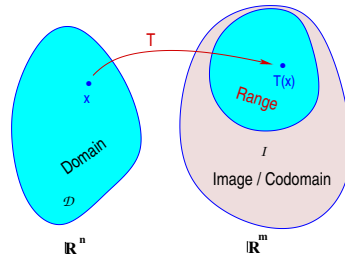
➤ The **range** of T is the set of all possible vectors of the form $T(x)$ for $x \in \mathcal{D}$.

➤ We say that T is **onto** if for every y in \mathcal{I} there is at least one x in \mathcal{D} such that $y = T(x)$.

➤ In other words T is **onto** if the range of T equals all of \mathcal{I}

➤ We say that T is **one-to-one** if for every y in \mathcal{I} there is at most one x in \mathcal{D} such that $y = T(x)$.

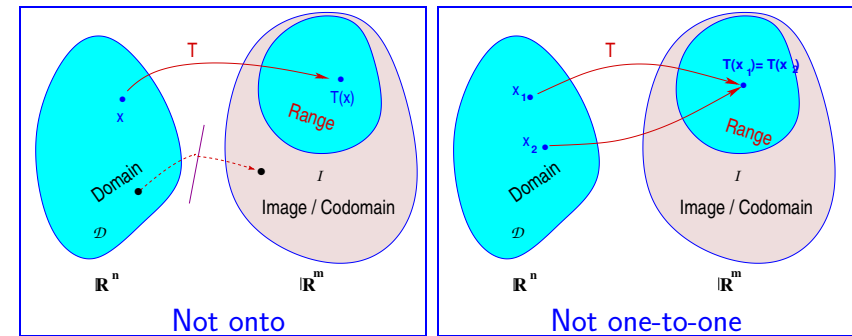
➤ In other words if $T(u_1) = T(u_2)$ then we must have $u_1 = u_2$



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Text:1.8-9 – Mappings

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➤ Now consider linear mappings: let T represented by a matrix A

➤ Now: Domain \mathcal{D} is all of \mathbb{R}^n and Image set \mathcal{I} is all of \mathbb{R}^m .


➤ So: A is one-to-one when every y in \mathbb{R}^m is 'reached' by A , i.e., if every y in \mathbb{R}^m can be written as $y = Ax$ for some $x \in \mathbb{R}^n$. Since Ax is a linear combination of the columns of A , this means that:

➤ A is onto iff the span of the columns of A equals \mathbb{R}^m

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Text:1.8-9 – Mappings

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 Show that A is one-to-one iff the columns of A are linearly independent.

 Find a 3×3 example of a mapping that is not onto

 Find a 3×3 example of a mapping that is not one-to-one.

MATRIX OPERATIONS [2.1]

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Text:1.8-9 – Mappings

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Matrix operations

- If A is an $m \times n$ matrix (m rows and n columns) –then the scalar entry in the i th row and j th column of A is denoted by a_{ij} and is called the (i, j) -entry of A .

$$\begin{array}{c} \text{Column } j \\ \downarrow \\ \text{Row } i \rightarrow \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & \boxed{a_{ij}} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{bmatrix} = A \\ \begin{array}{ccc} \uparrow & \uparrow & \uparrow \\ a_1 & a_j & a_n \end{array} \end{array}$$

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Text: 2.1 – Matrix

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- The number a_{ij} is the i th entry (from the top) of the j th column
- Each column of A is a list of m real numbers, which identifies a vector in \mathbb{R}^m called a **column vector**
- The columns are denoted by a_1, \dots, a_n , and the matrix A is written as $A = [a_1, a_2, \dots, a_n]$

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Text: 2.1 – Matrix

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- The **diagonal entries** in an $m \times n$ matrix A are $a_{11}, a_{22}, a_{33}, \dots$, and they form the main diagonal of A .
- A **diagonal matrix** is a matrix whose nondiagonal entries are zero
- An important example is the $n \times n$ **identity matrix**, I_n (each diagonal entry equals one) - Example:

$$I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- Another important matrix is the **zero matrix** (all entries are 0). It is denoted by O .

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Text: 2.1 – Matrix

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Equality of two matrices: Two matrices A and B are equal if they have the same size (they are both $m \times n$) and if their entries are all the same.

$$a_{ij} = b_{ij} \quad \text{for all } i = 1, \dots, m, \quad j = 1, \dots, n$$

Sum of two matrices: If A and B are $m \times n$ matrices, then their sum $A + B$ is the $m \times n$ matrix whose entries are the sums of the corresponding entries in A and B .

- If we call C this sum we can write:

$$c_{ij} = a_{ij} + b_{ij} \quad \text{for all } i = 1, \dots, m, \quad j = 1, \dots, n$$



$$\begin{bmatrix} 4 & 0 & 5 \\ 1 & 3 & 2 \end{bmatrix} + \begin{bmatrix} 3 & 1 & -3 \\ 0 & 2 & -2 \end{bmatrix} = ??; \quad \begin{bmatrix} 4 & 0 & 5 \\ 1 & 3 & 2 \end{bmatrix} + \begin{bmatrix} 1 & -3 \\ 2 & -2 \end{bmatrix} = ??$$

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Text: 2.1 – Matrix

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scalar multiple of a matrix If r is a scalar and A is a matrix, then the scalar multiple rA is the matrix whose entries are r times the corresponding entries in A .

$$(\alpha A)_{ij} = \alpha a_{ij} \quad \text{for all } i = 1, \dots, m, \quad j = 1, \dots, n$$

Theorem Let A , B , and C be matrices of the same size, and let α and β be scalars. Then

- $A + B = B + A$
- $(A + B) + C = A + (B + C)$
- $A + 0 = A$
- $\alpha(A + B) = \alpha A + \alpha B$
- $(\alpha + \beta)A = \alpha A + \beta A$
- $\alpha(\beta A) = (\alpha\beta)A$

 Prove all of the above equalities

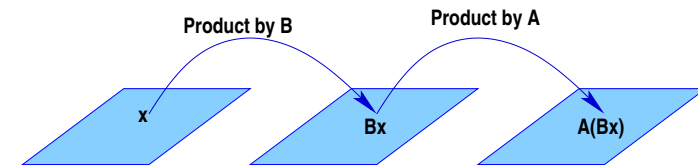
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Text: 2.1 – Matrix

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Matrix Multiplication

- When a matrix B multiplies a vector x , it transforms x into the vector Bx .
- If this vector is then multiplied in turn by a matrix A , the resulting vector is $A(Bx)$.



- Thus $A(Bx)$ is produced from x by a **composition** of mappings—the linear transformations induced by B and A .
- Note: $x \rightarrow yA(Bx)$ is a linear mapping (prove this).

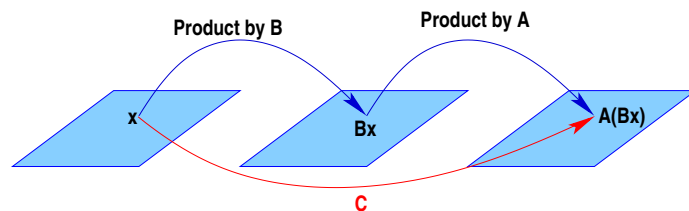
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Text: 2.1 – Matrix

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Goal: to represent this composite mapping as a multiplication by a single matrix, call it C for now, so that

$$A(Bx) = Cx$$



- Assume A is $m \times n$, B is $n \times p$, and x is in \mathbb{R}^p
- Denote the columns of B by b_1, \dots, b_p and the entries in x by x_1, \dots, x_p . Then:

$$Bx = x_1 b_1 + \dots + x_p b_p$$

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Text: 2.1 – Matrix

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- By the linearity of multiplication by A :
$$A(Bx) = A(x_1 b_1) + \dots + A(x_p b_p) = x_1 A b_1 + \dots + x_p A b_p$$

- The vector $A(Bx)$ is a linear combination of Ab_1, \dots, Ab_p , using the entries in x as weights.

- In matrix notation, this linear combination is written as

$$A(Bx) = [Ab_1, Ab_2, \dots, Ab_p] \cdot x$$

- Thus, multiplication by $[Ab_1, Ab_2, \dots, Ab_p]$ transforms x into $A(Bx)$.

- Therefore the desired matrix C is the matrix

$$C = [Ab_1, Ab_2, \dots, Ab_p]$$

- Denoted by AB

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Text: 2.1 – Matrix

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Definition: If A is an $m \times n$ matrix, and if B is an $n \times p$ matrix with columns b_1, \dots, b_p , then the product AB is the matrix whose p columns are Ab_1, \dots, Ab_p . That is:

$$AB = A[b_1, b_2, \dots, b_p] = [Ab_1, Ab_2, \dots, Ab_p]$$

► Important to remember that :

Multiplication of matrices corresponds to composition of linear transformations.

 Operation count: How many operations are required to perform product AB ?

 Compute AB when

$$A = \begin{bmatrix} 2 & -1 \\ 1 & 3 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 2 & -1 \\ 1 & 3 & -2 \end{bmatrix}$$

 Compute AB when

$$A = \begin{bmatrix} 2 & -1 & 2 & 0 \\ 1 & -2 & 1 & 0 \\ 3 & -2 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 1 & -1 & -2 \\ 0 & -2 & 2 \\ 2 & 1 & -2 \\ -1 & 3 & 2 \end{bmatrix}$$


 Can you compute AB when


$$A = \begin{bmatrix} 2 & -1 \\ 1 & 3 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 2 \\ 1 & 3 \\ -1 & 4 \end{bmatrix} ?$$

Row-wise matrix product

► Recall what we did with matrix-vector product to compute a single entry of the vector Ax

► Can we do the same thing here? i.e., How can we compute the entry c_{ij} of the product AB without computing entire columns?

 Do this to compute entry $(2, 2)$ in the first example above.


 Operation counts: Is more or less expensive to perform the matrix-vector product row-wise instead of column-wise?

Properties of matrix multiplication

Theorem Let A be an $m \times n$ matrix, and let B and C have sizes for which the indicated sums and products are defined.

- $A(BC) = (AB)C$ (associative law of multiplication)
- $A(B + C) = AB + AC$ (left distributive law)
- $(B + C)A = BA + CA$ (right distributive law)
- $\alpha(AB) = (\alpha A)B = A(\alpha B)$ for any scalar α
- $I_m A = A I_n = A$ (product with identity)

 If $AB = AC$ then $B = C$ ('simplification') : True-False?

 If $AB = 0$ then either $A = 0$ or $B = 0$: True or False?

 $AB = BA$: True or false??

Square matrices. Matrix powers

- Important particular case when $n = m$ - so matrix is $n \times n$
- In this case if x is in \mathbb{R}^n then $y = Ax$ is also in \mathbb{R}^n
- AA is also a square $n \times n$ matrix and will be denoted by A^2
- More generally, the matrix A^k is the matrix which is the product of k copies of A :

$$A^1 = A; \quad A^2 = AA; \quad \dots \quad A^k = \underbrace{A \cdots A}_{k \text{ times}}$$

- For consistency define A^0 to be the identity: $A^0 = I_n$,

☞ $A^l \times A^k = A^{l+k}$ - Also true when k or l is zero.

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Text: 2.1 - Matrix

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Transpose of a matrix

Given an $m \times n$ matrix A , the **transpose** of A is the $n \times m$ matrix, denoted by A^T , whose columns are formed from the corresponding rows of A .

Theorem : Let A and B denote matrices whose sizes are appropriate for the following sums and products.

- $(A^T)^T = A$
- $(A + B)^T = A^T + B^T$
- $(\alpha A)^T = \alpha A^T$ for any scalar α
- $(AB)^T = B^T A^T$

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Text: 2.1 - Matrix

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More on matrix products

- Recall: Product of the matrix A by the vector x :

$$\begin{matrix} y \\ \left[\begin{matrix} \beta_1 \\ \vdots \\ \beta_j \\ \vdots \\ \beta_n \end{matrix} \right] \end{matrix} = \begin{matrix} A \\ \left[\begin{matrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{matrix} \right] \end{matrix} \begin{matrix} x \\ \left[\begin{matrix} \alpha_1 \\ \vdots \\ \alpha_j \\ \vdots \\ \alpha_n \end{matrix} \right] \end{matrix}$$

$$= \alpha_1 a_1 + \alpha_2 a_2 + \cdots + \alpha_n a_n$$

- x, y are vectors; y is the result of $A \times x$.
- a_1, a_2, \dots, a_n are the columns of A

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Text: 2.1 - Matrix2

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- $\alpha_1, \alpha_2, \dots, \alpha_n$ are the components of x [scalars]
- $\alpha_1 a_1$ is the first column of A multiplied by the scalar α_1 which is the first component of x .
- $\alpha_1 a_1 + \alpha_2 a_2 + \cdots + \alpha_n a_n$ is a linear combination of a_1, a_2, \dots, a_n with weights $\alpha_1, \alpha_2, \dots, \alpha_n$.

- This is the 'column-wise' form of the 'matvec'

Example: $A = \begin{bmatrix} 1 & 2 & -1 \\ 0 & -1 & 3 \end{bmatrix} \quad x = \begin{bmatrix} -2 \\ 1 \\ -3 \end{bmatrix} \quad y = ?$

- Result:

$$y = -2 \times \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 1 \times \begin{bmatrix} 2 \\ -1 \end{bmatrix} - 3 \times \begin{bmatrix} -1 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ -10 \end{bmatrix}$$

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Text: 2.1 - Matrix2

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- Can get i -th component of the result y without the others:

$$\beta_i = \alpha_1 a_{i1} + \alpha_2 a_{i2} + \cdots + \alpha_n a_{in}$$

Example: In the above example extract β_2

$$\beta_2 = (-2) \times 0 + (1) \times (-1) + (-3) \times (3) = -10$$

- Can compute $\beta_1, \beta_2, \dots, \beta_m$ in this way.
- This is the 'row-wise' form of the 'matvec'

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Text: 2.1 – Matrix2

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Matrix-Matrix product

- When A is $m \times n$, B is $n \times p$, the product AB of the matrices A and B is the $m \times p$ matrix defined as

$$AB = [Ab_1, Ab_2, \dots, Ab_p]$$

- Each Ab_j is a matrix-vector product: the product of A by the j -th column of B . Matrix AB has dimension $m \times p$
- Can use what we know on matvecs to perform the product

1. Column form – In words: “The j -th column of AB is a linear combination of the columns of A , with weights $b_{1j}, b_{2j}, \dots, b_{nj}$ ” (entries of j -th col. of B)

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Text: 2.1 – Matrix2

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Example: $A = \begin{bmatrix} 1 & 2 & -1 \\ 0 & -1 & 3 \end{bmatrix}$ $B = \begin{bmatrix} -2 & 1 \\ 1 & -2 \\ -3 & 2 \end{bmatrix}$ $AB = ?$

Result: $B = \begin{bmatrix} \begin{bmatrix} 1 & 2 & -1 \\ 0 & -1 & 3 \end{bmatrix} \begin{bmatrix} -2 \\ 1 \\ -3 \end{bmatrix}, \begin{bmatrix} 1 & 2 & -1 \\ 0 & -1 & 3 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \\ 2 \end{bmatrix} \end{bmatrix}$
 $= \begin{bmatrix} 3 & -6 \\ -10 & 8 \end{bmatrix}$

- First column has been computed before: it is equal to:
 $(-2) \times (\text{col. 1 of } A) + (1) \times (\text{col. 2 of } A) + (-3) \times (\text{col. 3 of } A)$
- Second column is equal to:
 $(1) \times (\text{col. 1 of } A) + (-2) \times (\text{col. 2 of } A) + (2) \times (\text{col. 3 of } A)$

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Text: 2.1 – Matrix2

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2. If we call C the matrix $C = AB$ what is c_{ij} ? From above:

$$c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots + a_{ik}b_{kj} + \cdots + a_{in}b_{nj}$$

- Fix j and run $i \rightarrow$ column-wise form just seen

3. Fix i and run $j \rightarrow$ row-wise form

Example: Get second row of AB in previous example.

$$c_{2j} = a_{21}b_{1j} + a_{22}b_{2j} + a_{23}b_{3j}, \quad j = 1, 2$$

- Can be read as : $c_{2j} = a_{21}b_{1j} + a_{22}b_{2j} + a_{23}b_{3j}$, or in words:
row2 of $C = a_{21}$ (row1 of B) + a_{22} (row2 of B) + a_{23} (row3 of B)
 $= 0$ (row1 of B) + (-1) (row2 of B) + (3) (row3 of B)
 $= [-10 \quad 8]$

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Text: 2.1 – Matrix2

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