

§2.1: Matrix Operations

We have several ways to combine functions to make new functions:

- Addition: if f, g have the same domains and codomains, then we can set $(f + g)\mathbf{x} = f(\mathbf{x}) + g(\mathbf{x})$,
- Composition: if the codomain of f is the domain of g , then we can set $(g \circ f)\mathbf{x} = g(f(\mathbf{x}))$,
- Inverse (§2.2): if f is one-to-one and onto, then we can set $f^{-1}(\mathbf{y})$ to be the unique solution to $f(\mathbf{x}) = \mathbf{y}$.

It turns out that the sum, composition and inverse of linear transformations are also linear (exercise: prove it!), and we can ask how the standard matrix of the new function is related to the standard matrices of the old functions.

Notation:

The (i, j) -entry of a matrix A is the entry in row i , column j , and is written a_{ij} or $(A)_{ij}$.

The **diagonal entries** of A are the entries a_{11}, a_{22}, \dots .

A **square matrix** has the same number of rows as columns. The associated linear transformation has the same domain and codomain.

A **diagonal matrix** is a square matrix whose **nondiagonal entries** are 0.

The **identity matrix** I_n is the $n \times n$ matrix whose **diagonal entries are 1** and whose nondiagonal entries are 0.

It is the standard matrix for the **identity transformation** $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ given by $T(\mathbf{x}) = \mathbf{x}$.

e.g.
$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \\ a_{41} & a_{42} & a_{43} \end{bmatrix}$$

e.g.
$$\begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

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

Addition:

If A, B are the standard matrices for some linear transformations $S, T : \mathbb{R}^n \rightarrow \mathbb{R}^m$, then $(S + T)\mathbf{x} = S(\mathbf{x}) + T(\mathbf{x})$ is a linear transformation. What is its standard matrix $A + B$?

Proceed column by column:

First column of the standard matrix of $S + T$
 $= (S + T)(\mathbf{e}_1)$ definition of standard matrix of $S + T$

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i.e. $(i, 1)$ -entry of $A + B = a_{i1} + b_{i1}$.

The same is true of all the other columns, so $(A + B)_{ij} = a_{ij} + b_{ij}$.

Example: $A = \begin{bmatrix} 4 & 0 & 5 \\ -1 & 3 & 2 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 1 & 1 \\ 3 & 5 & 7 \end{bmatrix}, \quad A + B = \begin{bmatrix} 5 & 1 & 6 \\ 2 & 8 & 9 \end{bmatrix}.$

Scalar multiplication:

If A is the standard matrix for a linear transformation $S : \mathbb{R}^n \rightarrow \mathbb{R}^m$, and c is a scalar, then $(cS)\mathbf{x} = c(S\mathbf{x})$ is a linear transformation. What is its standard matrix cA ?

Proceed column by column:

First column of the standard matrix of cS

$$= (cS)(\mathbf{e}_1)$$

definition of standard matrix of cS

$$= c(S\mathbf{e}_1)$$

definition of cS

$$= \text{first column of } A \text{ multiplied by } c.$$

definition of standard matrix of S

i.e. $(i, 1)$ -entry of $cA = ca_{i1}$.

The same is true of all the other columns, so $(cA)_{ij} = ca_{ij}$.

Example: $A = \begin{bmatrix} 4 & 0 & 5 \\ -1 & 3 & 2 \end{bmatrix}, \quad c = -3, \quad cA = \begin{bmatrix} -12 & 0 & -15 \\ 3 & -9 & -6 \end{bmatrix}.$

Addition and scalar multiplication satisfy some familiar rules of arithmetic:

Let A , B , and C be matrices of the same size, and let r and s be scalars. Then

a. $A + B = B + A$

d. $r(A + B) = rA + rB$

b. $(A + B) + C = A + (B + C)$

e. $(r + s)A = rA + sA$

c. $A + 0 = A$

f. $r(sA) = (rs)A$

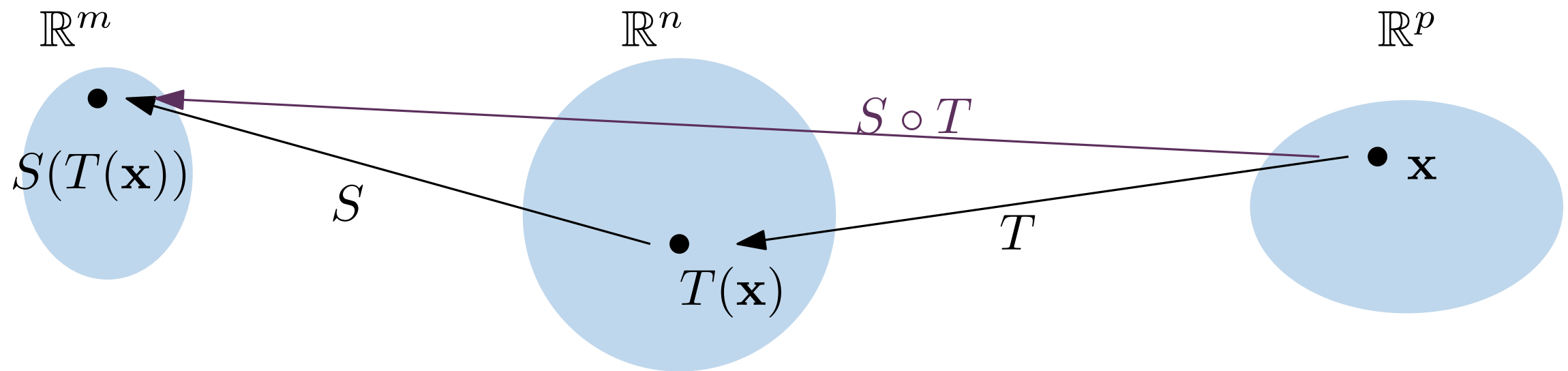
0 denotes the **zero matrix**:

$$0 = \begin{bmatrix} 0 & \cdots & 0 & \cdots & 0 \\ \vdots & & & & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}$$

Composition:

If A is the standard matrix for a linear transformation $S : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and B is the standard matrix for a linear transformation $T : \mathbb{R}^p \rightarrow \mathbb{R}^n$ then the composition $S \circ T$ (T first, then S) is linear.

What is its standard matrix AB ?



A is a $m \times n$ matrix,

B is a $n \times p$ matrix,

AB is a $m \times p$ matrix - so the (i, j) -entry of AB cannot simply be $a_{ij}b_{ij}$.

Composition:

Proceed column by column:

$$\begin{aligned} & \text{First column of the standard matrix of } S \circ T \\ &= (S \circ T)(\mathbf{e}_1) \\ &= S(T(\mathbf{e}_1)) \\ &= S(\mathbf{b}_1) \quad (\text{writing } \mathbf{b}_j \text{ for column } j \text{ of } B) \\ &= A\mathbf{b}_1, \text{ and similarly for the other columns.} \end{aligned}$$

$$\text{So} \quad AB = A \begin{bmatrix} | & | & | \\ \mathbf{b}_1 & \dots & \mathbf{b}_p \\ | & | & | \end{bmatrix} = \begin{bmatrix} | & | & | \\ A\mathbf{b}_1 & \dots & A\mathbf{b}_p \\ | & | & | \end{bmatrix}.$$

The j th column of AB is a linear combination of the columns of A using weights from the j th column of B .

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Another view is the row-column method: the (i, j) -entry of AB is $a_{i1}b_{1j} + a_{i2}b_{2j} + \dots + a_{in}b_{nj}$.

Some familiar rules of arithmetic hold for matrix multiplication...

Let A be $m \times n$ and let B and C have sizes for which the indicated sums and products are defined (different sizes for each statement).

a. $A(BC) = (AB)C$ (associative law of multiplication)

b. $A(B + C) = AB + AC$ (left - distributive law)

c. $(B + C)A = BA + CA$ (right-distributive law)

d. $r(AB) = (rA)B = A(rB)$
for any scalar r

e. $I_m A = A = A I_n$ (identity for matrix multiplication)

... but not all of them:

- Usually, $AB \neq BA$ (because order matters for function composition: $S \circ T \neq T \circ S$);
- It is possible for $AB = 0$ even if $A \neq 0$ and $B \neq 0$.

A fun application of matrix multiplication:

Consider rotations counterclockwise about the origin.

Rotation through $(\theta + \varphi) = (\text{rotation through } \theta) \circ (\text{rotation through } \varphi)$.

$$\begin{aligned} \begin{bmatrix} \cos(\theta + \varphi) & -\sin(\theta + \varphi) \\ \sin(\theta + \varphi) & \cos(\theta + \varphi) \end{bmatrix} &= \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \cos \varphi & -\sin \varphi \\ \sin \varphi & \cos \varphi \end{bmatrix} \\ &= \begin{bmatrix} \cos \theta \cos \varphi - \sin \theta \sin \varphi & -\cos \theta \sin \varphi - \sin \theta \cos \varphi \\ \sin \theta \cos \varphi + \cos \theta \sin \varphi & -\sin \theta \sin \varphi + \cos \theta \cos \varphi \end{bmatrix}. \end{aligned}$$

So, equating the entries in the first column:

$$\cos(\theta + \varphi) = \cos \theta \cos \varphi - \sin \theta \sin \varphi$$

$$\sin(\theta + \varphi) = \cos \theta \sin \varphi + \sin \theta \cos \varphi$$

Powers:

For a square matrix A , the k th power of A is $A^k = \underbrace{A \dots A}_{k \text{ times}}$.

If A is the standard matrix for a linear transformation T , then A^k is the standard matrix for T^k , the function that “applies T k times”.

Examples:

$$\begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix}^3 = \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix} \left(\begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix} \right) = \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix} \begin{bmatrix} 7 & 2 \\ 3 & 6 \end{bmatrix} = \begin{bmatrix} 13 & 14 \\ 21 & 6 \end{bmatrix}.$$

$$\begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix}^3 = \begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix} \left(\begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix} \right) = \begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} 9 & 0 \\ 0 & 4 \end{bmatrix} = \begin{bmatrix} 27 & 0 \\ 0 & -8 \end{bmatrix} = \begin{bmatrix} 3^3 & 0 \\ 0 & (-2)^3 \end{bmatrix}.$$

Exercise: show that $\begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}^k = \begin{bmatrix} a_{11}^k & 0 \\ 0 & a_{22}^k \end{bmatrix}$, and similarly for larger diagonal matrices.

We can consider polynomials involving square matrices:

Example: Let $p(x) = x^3 - 2x^2 + x - \textcircled{2}$ and $A = \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix}$, $D = \begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix}$ as on the previous page. Then use the identity matrix instead of constants

$$p(A) = A^3 - 2A^2 + A - \textcircled{2I_2} = \begin{bmatrix} 13 & 14 \\ 21 & 6 \end{bmatrix} - \begin{bmatrix} 14 & 4 \\ 6 & 12 \end{bmatrix} + \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix} - \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} -2 & 12 \\ 18 & -8 \end{bmatrix}.$$

$$p(D) = D^3 - 2D^2 + D - 2I_2 = \begin{bmatrix} 27 & 0 \\ 0 & -8 \end{bmatrix} - \begin{bmatrix} 18 & 0 \\ 0 & 8 \end{bmatrix} + \begin{bmatrix} 3 & 0 \\ 0 & -2 \end{bmatrix} - \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 10 & 0 \\ 0 & -20 \end{bmatrix} = \begin{bmatrix} p(3) & 0 \\ 0 & p(2) \end{bmatrix}.$$

For a polynomial involving a single matrix, we can factorise and expand as usual:

Example: $x^3 - 2x^2 + x - 2 = (x^2 + 1)(x - 2)$, and

$$(A^2 + I_2)(A - 2I_2) = \begin{bmatrix} 8 & 2 \\ 3 & 7 \end{bmatrix} \begin{bmatrix} -1 & 2 \\ 3 & -2 \end{bmatrix} = \begin{bmatrix} -2 & 12 \\ 18 & -8 \end{bmatrix}.$$

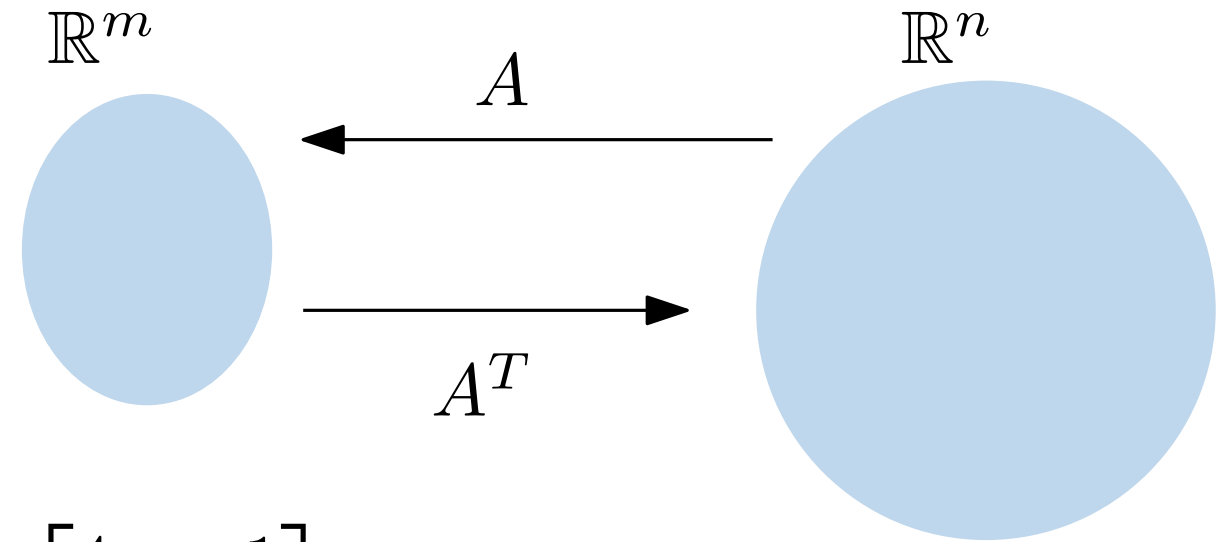
But be careful with the order when there are two or more matrices:

Example: $x^2 - y^2 = (x + y)(x - y)$, but

$$(A + D)(A - D) = A^2 - AD + DA - D^2 \neq A^2 - D^2.$$

Transpose:

The transpose of A is the matrix A^T whose (i, j) -entry is a_{ji} .
i.e. we obtain A^T by “flipping A through the main diagonal”.



Example: $A = \begin{bmatrix} 4 & 0 & 5 \\ -1 & 3 & 2 \end{bmatrix}, \quad A^T = \begin{bmatrix} 4 & -1 \\ 0 & 3 \\ 5 & 2 \end{bmatrix}.$

We will be interested in square matrices A such that

$A = A^T$ (**symmetric matrix**, self-adjoint linear transformation, §7.1), or

$A = -A^T$ (**skew-symmetric matrix**), or

$A^{-1} = A^T$ (**orthogonal matrix**, or isometric linear transformation, §6.2).

Properties of the transpose:

Let A and B denote matrices whose sizes are appropriate for the following sums and products (different sizes for each statement).

a. $(A^T)^T =$

b. $(A + B)^T =$

c. For any scalar r , $(rA)^T =$

d. $(AB)^T =$

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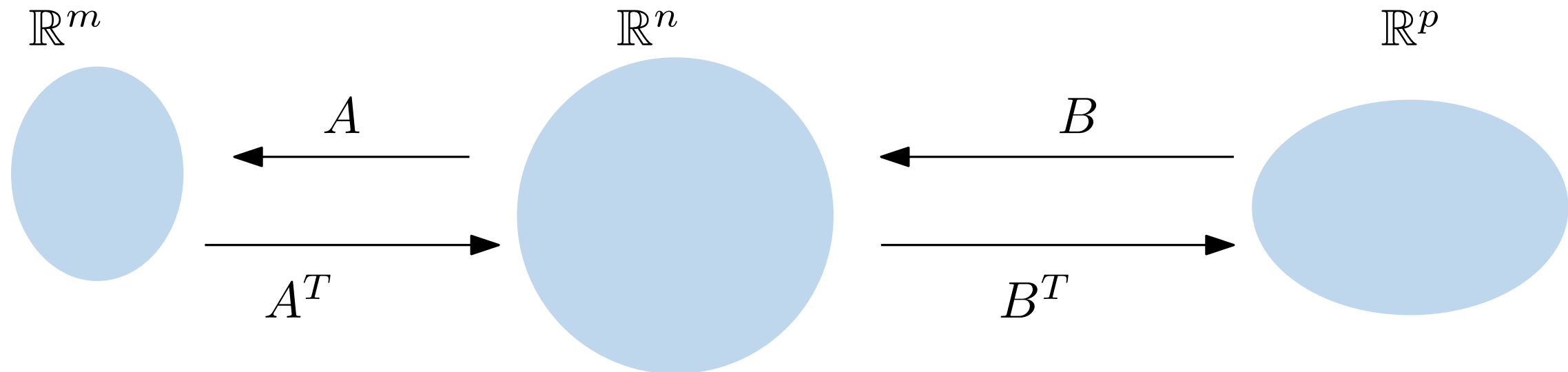
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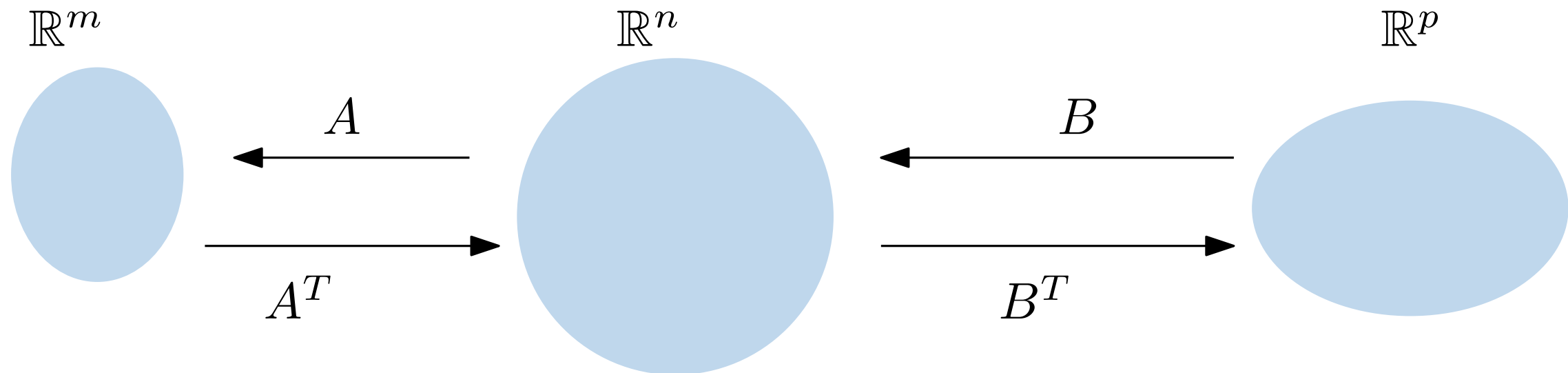
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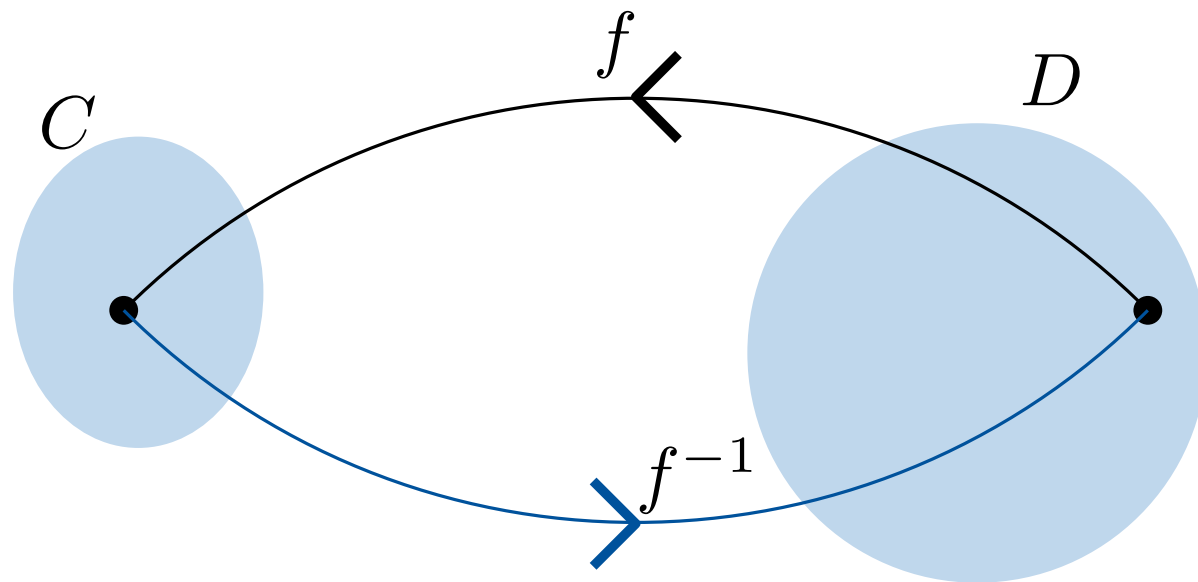
Proof: (i, j) -entry of $(AB)^T = (j, i)$ -entry of AB

$$= a_{j1}b_{1i} + a_{j2}b_{2i} \cdots + a_{jn}b_{ni}$$
$$= (A^T)_{1j}(B^T)_{i1} + (A^T)_{2j}(B^T)_{i2} \cdots + (A^T)_{nj}(B^T)_{in}$$
$$= (i, j)\text{-entry of } B^T A^T.$$

§2.2: The Inverse of a Matrix

Remember from calculus that the inverse of a function $f : D \rightarrow C$ is the function $f^{-1} : C \rightarrow D$ such that $f^{-1} \circ f = \text{identity map on } D$ and $f \circ f^{-1} = \text{identity map on } C$.

Equivalently, $f^{-1}(y)$ is the unique solution to $f(x) = y$.
So f^{-1} exists if and only if f is one-to-one and onto. Then we say f is **invertible**.



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Let T be a linear transformation whose standard matrix is A . From last week:

- T is one-to-one if and only if $\text{rref}(A)$ has a pivot in every
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Let T be a linear transformation whose standard matrix is A . From last week:

- T is one-to-one if and only if $\text{rref}(A)$ has a pivot in every column.
- T is onto if and only if $\text{rref}(A)$ has a pivot in every row.

So if T is invertible, then A must be a square matrix.

Warning: not all square matrices come from invertible linear transformations,

e.g. $\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$.

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Definition: A $n \times n$ matrix A is *invertible* if there is a $n \times n$ matrix C satisfying $CA = AC = I_n$.

Fact: A matrix C with this property is unique:
if $BA = AC = I_n$, then $BAC = BI_n = B$ and $BAC = I_nC = C$ so $B = C$.

The matrix C is called the *inverse* of A , and is written A^{-1} . So

$$A^{-1}A = AA^{-1} = I_n.$$

A matrix that is not invertible is sometimes called *singular*.

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Theorem 5: Solving linear systems with the inverse: If A is an invertible $n \times n$ matrix, then, for each \mathbf{b} in \mathbb{R}^n , the unique solution to $A\mathbf{x} = \mathbf{b}$ is $\mathbf{x} = A^{-1}\mathbf{b}$.

Proof: For any \mathbf{b} in \mathbb{R}^n , we have $A(A^{-1}\mathbf{b}) = \mathbf{b}$, so $\mathbf{x} = A^{-1}\mathbf{b}$ is a solution.

And, if \mathbf{u} is any solution, then $\mathbf{u} = A^{-1}(A\mathbf{u}) = A^{-1}\mathbf{b}$, so $A^{-1}\mathbf{b}$ is the unique solution.

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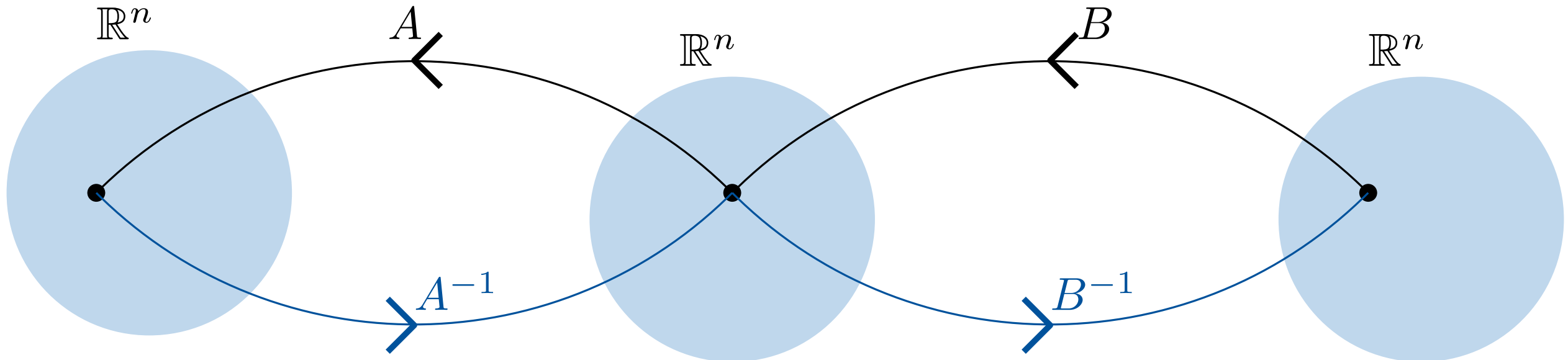
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In particular, if A is an invertible $n \times n$ matrix, then $\text{rref}(A) = I_n$.

Properties of the inverse:

Suppose A and B are invertible. Then the following results hold:

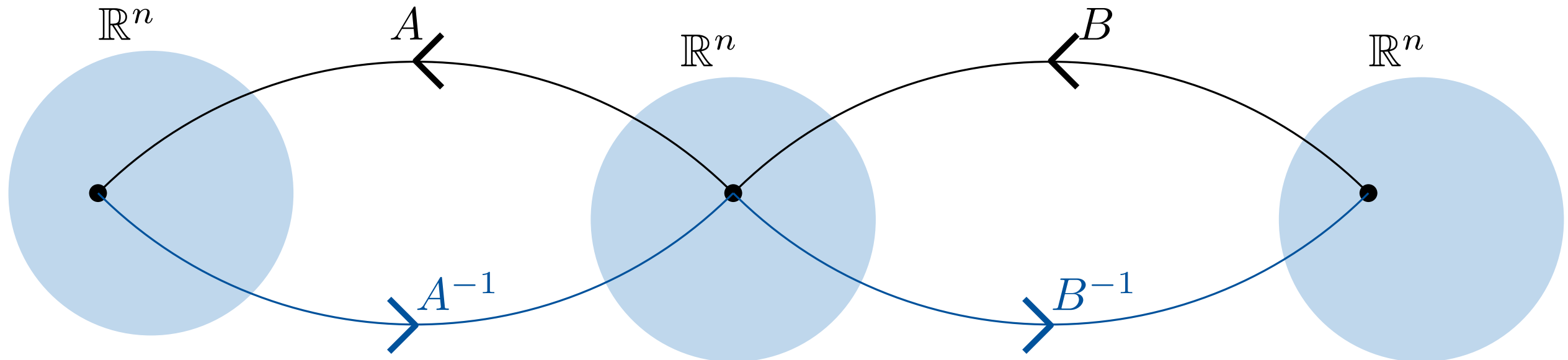
- a. A^{-1} is invertible and $(A^{-1})^{-1} = A$ (i.e. A is the inverse of A^{-1}).
- b. AB is invertible and $(AB)^{-1} = ?$
- c. A^T is invertible and $(A^T)^{-1} = (A^{-1})^T$



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- c. A^T is invertible and $(A^T)^{-1} = (A^{-1})^T$



Inverse of a 2×2 matrix:

Fact: Let $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$.

- i) if $ad - bc \neq 0$, then A is invertible and $A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$,
- ii) if $ad - bc = 0$, then A is not invertible.

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Proof of i):

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \left(\frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \right) = \frac{1}{ad - bc} \begin{bmatrix} ad - bc & -ab + ba \\ cd - dc & -cb + da \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

$$\left(\frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \right) \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \frac{1}{ad - bc} \begin{bmatrix} da - bc & db - bd \\ -ca + ac & -cb + ad \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

Proof of ii): next week.

Inverse of a 2×2 matrix:

Example: Let $A = \begin{bmatrix} \cos \varphi & -\sin \varphi \\ \sin \varphi & \cos \varphi \end{bmatrix}$, the standard matrix of rotation about the origin through an angle φ counterclockwise.

Example: Let $B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$, the standard matrix of projection to the x_1 -axis.

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$\cos \varphi \cos \varphi - (-\sin \varphi) \sin \varphi = \cos^2 \varphi + \sin^2 \varphi = 1$ so A is invertible, and

$A^{-1} = \frac{1}{1} \begin{bmatrix} \cos \varphi & \sin \varphi \\ -\sin \varphi & \cos \varphi \end{bmatrix} = \begin{bmatrix} \cos(-\varphi) & -\sin(-\varphi) \\ \sin(-\varphi) & \cos(-\varphi) \end{bmatrix}$, the standard matrix of rotation about the origin through an angle φ clockwise.

Example: Let $B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$, the standard matrix of projection to the x_1 -axis.

$1 \cdot 0 - 0 \cdot 0 = 0$ so B is not invertible.

Exercise: choose a matrix C that is the standard matrix of a reflection, and check that C is invertible and $C^{-1} = C$.

Inverse of a $n \times n$ matrix:

If A is the standard matrix of an invertible linear transformation T , then A^{-1} is the standard matrix of T^{-1} . So

$$A^{-1} = \left[\begin{array}{c|c|c} T^{-1}(\mathbf{e}_1) & \cdots & T^{-1}(\mathbf{e}_n) \\ \hline \end{array} \right].$$

$T^{-1}(\mathbf{e}_i)$ is the unique solution to the equation $T(\mathbf{x}) = \mathbf{e}_i$, or equivalently $A\mathbf{x} = \mathbf{e}_i$. So if we row-reduce the augmented matrix $[A|\mathbf{e}_i]$, we should get $[I_n|T^{-1}(\mathbf{e}_i)]$. (Remember $\text{rref}(A) = I_n$.)

We carry out this row-reduction for all \mathbf{e}_i at the same time:

$$[A|I_n] = \left[\begin{array}{c|c|c} A & \mathbf{e}_1 & \cdots & \mathbf{e}_n \\ \hline \end{array} \right] \xrightarrow{\text{row reduction}} \left[\begin{array}{c|c|c} I_n & T^{-1}(\mathbf{e}_1) & \cdots & T^{-1}(\mathbf{e}_n) \\ \hline \end{array} \right] = [I_n|A^{-1}].$$

We showed that, if A is invertible, then $[A|I_n]$ row-reduces to $[I_n|A^{-1}]$.
In other words, if we already knew that A was invertible, then we can find its inverse by row-reducing $[A|I_n]$.
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Indeed, we can:

Fact: If $[A|I_n]$ row-reduces to $[I_n|C]$, then A is invertible and $C = A^{-1}$.

Proof: (different from textbook, not too important)

If $[A|I_n]$ row-reduces to $[I_n|C]$, then \mathbf{c}_i is the unique solution to $A\mathbf{x} = \mathbf{e}_i$, so $AC\mathbf{e}_i = A\mathbf{c}_i = \mathbf{e}_i$ for all i , so $AC = I_n$.

Also, by switching the left and right sides, and reading the process backwards, $[C|I_n]$ row-reduces to $[I_n|A]$. So \mathbf{a}_i is the unique solution to $C\mathbf{x} = \mathbf{e}_i$, so $CA\mathbf{e}_i = C\mathbf{a}_i = \mathbf{e}_i$ for all i , so $CA = I_n$.

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In particular: an $n \times n$ matrix A is invertible if and only if $\text{rref}(A) = I_n$.

Also equivalent: $\text{rref}(A)$ has a pivot in every row and column.

For a square matrix, having a pivot in each row is the same as having a pivot in

§2.3: Characterisations of Invertible Matrices

As observed at the end of the previous page: for a square $n \times n$ matrix A , the following are equivalent:

- A is invertible.
- $\text{rref}(A) = I_n$.
- $\text{rref}(A)$ has a pivot in every row.
- $\text{rref}(A)$ has a pivot in every column.

This means that, in the very special case when A is a square matrix, all the statements in the Existence of Solutions Theorem (“green theorem”) and all the statements in the Uniqueness of Solutions Theorem (“red theorem”) are all equivalent, so we can put the two lists together to make a giant list of equivalent statements, on the next page. (The third list, in blue, comes from combining the corresponding green and red statements.) (Re the last line: you proved on ex. sheet #9 q2c,d that it implies the higher lines; exercise: prove that the higher lines imply it.)

Theorem 8: Invertible Matrix Theorem (IMT): For a square $n \times n$ matrix A , the following are equivalent:

$\text{rref}(A)$ has a pivot in every row.

$A\mathbf{x} = \mathbf{b}$ has at least one solution for each \mathbf{b} in \mathbb{R}^n .

The columns of A span \mathbb{R}^n .

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is onto.

There is a matrix D such that $AD = I_n$.

$\text{rref}(A)$ has a pivot in every column.

$A\mathbf{x} = \mathbf{0}$ has only the trivial solution.

The columns of A are linearly independent.

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is one-to-one.

There is a matrix C such that $CA = I_n$.

$\text{rref}(A) = I_n$.

$A\mathbf{x} = \mathbf{b}$ has a unique solution for each \mathbf{b} in \mathbb{R}^n .

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is an invertible function.

A is invertible.

We will add more statements to the Invertible Matrix Theorem throughout the class.

Important consequences:

- line 3: A set of n vectors in \mathbb{R}^n span \mathbb{R}^n if and only if the set is linearly independent.
- line 4: A linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ (i.e. same domain and codomain) is one-to-one if and only if it is onto.

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Example: Is the matrix $\begin{bmatrix} 1 & -1 & 4 \\ 2 & 0 & 8 \\ 3 & 8 & 12 \end{bmatrix}$ invertible?

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Example: Is the matrix $\begin{bmatrix} 1 & -1 & 4 \\ 2 & 0 & 8 \\ 3 & 8 & 12 \end{bmatrix}$ invertible?

Answer: No: the third column is 4 times the first column, so the columns are not linearly independent. So the matrix is not invertible

We also know that $A\mathbf{x} = \mathbf{b}$ can never have a unique solution.

Theorem 8: Invertible Matrix Theorem continued: A is invertible if and only if A^T is invertible. (Proof: Check that $(A^T)^{-1} = (A^{-1})^T$.)

This means that the statements in the Invertible Matrix Theorem are equivalent to the corresponding statements with “row” instead of “column”, for example:

- The columns of an $n \times n$ matrix are linearly independent if and only if its rows span \mathbb{R}^n . (This is in fact also true for rectangular matrices.)
- If A is a square matrix and $A\mathbf{x} = \mathbf{b}$ has a unique solution for some \mathbf{b} , then the rows of A are linearly independent.

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Advanced application (important for probability):

Let A be a square matrix. If the entries in each column of A sum to 1, then there is a nonzero vector \mathbf{v} such that $A\mathbf{v} = \mathbf{v}$.

$$\text{Hint: } (A - I)^T \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \mathbf{0}.$$