

# Mathematics for Artificial Intelligence

## Square Matrices and Related Matters

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# Outline

## 1 Square Matrices

- Introduction
- The Inverse
- Solution to  $A\mathbf{x} = \mathbf{y}$
- Algorithm for the Inverse of a Matrix

## 2 Determinants

- Introduction
- Complexity Increases
- Reducing the Complexity
- Some Consequences of the definition
- Special Determinants



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# Square Matrices

## Observation

Square matrices are the only matrices that can have inverses.

## Further

In a system of linear algebraic equations:

- 1 If the number of equations equals the number of unknowns
- 2 Then the associated coefficient matrix  $A$  is square.

## Now use the Gauss-Jordan

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# We have two possibilities

## First case

The Gauss-Jordan form for  $A_{n \times n}$  is the  $n \times n$  identity matrix  $I_n$

## Second case

The Gauss-Jordan form for  $A$  has at least one row of zeros





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# Explanation

In the first case

We can show that  $A$  is invertible.

How? Do you remember?

$$E_k E_{k-1} \dots E_2 E_1 A = I,$$

Setting  $B = E_k E_{k-1} \dots E_2 E_1$

We have  $BA = I$  therefore  $B = A^{-1}$



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## Furthermore

We can build the following matrix

$$E_1^{-1} E_2^{-1} \cdots E_k^{-1}$$

Then

$$\left(E_1^{-1} E_2^{-1} \cdots E_k^{-1}\right) BA = \left(E_1^{-1} E_2^{-1} \cdots E_k^{-1}\right) I$$

Thus

$$\left(E_1^{-1} E_2^{-1} \cdots E_k^{-1}\right) (E_k E_{k-1} \cdots E_2 E_1) A = \left(E_1^{-1} E_2^{-1} \cdots E_k^{-1}\right)$$



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We have

$$A = \left( E_1^{-1} E_2^{-1} \cdots E_k^{-1} \right)$$

Theorem

The following are equivalent:

- 1 The square matrix  $A$  is invertible.
- 2 The Gauss-Jordan or reduced echelon form of  $A$  is the identity matrix.
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# The Second Case

## The Gauss-Jordan form of $A_{n \times n}$

- It can only have at most  $n$  leading entries.

If the Gauss-Jordan form of  $A$  is not  $I_n$

- We have something quite different

Then the GJ form has  $n - r$  or fewer leading entries

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# Example

Given

$$A = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}$$

What do we need to do?

Look at the blackboard...

Therefore

$$A^{-1} = E_4 E_3 E_2 E_1$$



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- Solutions to the system exist, but there are infinitely many.



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# Something Quite Important

We have done something important

It leads immediately to an algorithm for constructing the inverse of  $A$ .

Observation

Suppose  $B_{n \times p}$  is another matrix with the same number of rows as  $A_{n \times n}$

Then

$$C = (A|B)_{n \times (n+p)}$$



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It is obvious

$$EC = (EA|EB)_{n \times (n+p)}$$

where

- $EA$  is a  $n \times n$  matrix.
- $EB$  is a  $n \times p$  matrix



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# Algorithm

Form the partitioned matrix

$$C = (A|I)$$

Apply the Gauss-Jordan reduction

$$E_k E_{k-1} \cdots E_1 (A|I) = (E_k E_{k-1} \cdots E_1 A | E_k E_{k-1} \cdots E_1 I)$$

Therefore, if  $A$  is invertible

$$(E_k E_{k-1} \cdots E_1 A | E_k E_{k-1} \cdots E_1 I) = (I | A^{-1})$$



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## Remark

The individual factors in the product of  $A^{-1}$  are not unique  
They depend on how we do the row reduction.



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## Before the Matrix we had the Determinant

You have seen determinants in your classes long ago

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \implies \det(A) = ad - bc$$

What about

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

Then

$$\det(A) = a_{11}a_{22}a_{33} + a_{12}a_{21}a_{32} + a_{13}a_{23}a_{31} - \dots \\ - a_{12}a_{21}a_{33} - a_{11}a_{23}a_{32} - a_{13}a_{22}a_{31}$$

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# Recursive Definition

## Definition

Let  $A$  be a  $n \times n$  matrix. Then the determinant of  $A$  is defined as follow:

$$\det(A) = \begin{cases} a_{11} & \text{if } n = 1 \\ \sum_{i=1}^n a_{i1} A_{i1} & \text{if } n > 1 \end{cases}$$

Where

$A_{ij}$  is the  $(i, j)$ -cofactor where

$$A_{ij} = (-1)^{i+j} \det(M_{ij})$$

Here

$M_{ij}$  is the  $(n-1) \times (n-1)$  matrix obtained from  $A$  by removing its  $i^{\text{th}}$  row and  $j^{\text{th}}$  column.

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# Example

We have

$$\begin{pmatrix} 1 & 1 & 1 \\ 0 & 2 & 1 \\ 0 & 0 & 3 \end{pmatrix}$$



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We have that for a  $A_{n \times n}$

$\det(A)$  has  $n$  factorials ( $n!$ ) terms

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The fastest computer of the world will take forever to finish



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Thus, we have some problems with that

## Floating point arithmetic

It is not at all the same thing as working with real numbers.

Representation

$$x = (d_1d_2d_3 \cdots d_n) \times 2^{a_1a_2 \cdots a_m} \quad (1)$$

The problem is at the round off

When we do a calculation on a computer, we almost never get the right answer.



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We would love the floating points to be represented uniformly

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- 2 multiplications and 1 addition to compute the  $2 \times 2$  determinant
- 12 multiplications and 5 additions to compute the  $3 \times 3$  determinant
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# Therefore

How do we avoid to get us into problems?

We need to define our determinant as a different structure...

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The determinant of  $A$  is a real-valued function of the rows of  $A$  which we write as

$$\det(A) = \det(r_1, r_2, \dots, r_n)$$



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# Properties

Multiplying a row by the constant  $c$  multiplies the determinant by  $c$

$$\det(\mathbf{r}_1, \mathbf{r}_2, \dots, c\mathbf{r}_i, \dots, \mathbf{r}_n) = c \det(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_i, \dots, \mathbf{r}_n)$$

If row  $i$  is the sum of the two row vectors  $\mathbf{x}$  and  $\mathbf{y}$

$$\det(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{x} + \mathbf{y}, \dots, \mathbf{r}_n) = \det(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{x}, \dots, \mathbf{r}_n) + \dots \\ \det(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{y}, \dots, \mathbf{r}_n)$$

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The determinant is a linear function of each row.



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## Further

Interchanging any two rows of the matrix changes the sign of the determinant

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Finally,

The determinant of any identity matrix is 1



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① if  $A = (\dots, 0, \dots)$ , also  $A = (\dots, c0, \dots)$

②  $\det(A) = c \times \det(A)$  for any  $c$

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Quite easy (Hint sing being reversed).



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If  $B$  is obtained from  $A$  by replacing  $r_i$  with  $r_i + cr_j$ , then  $\det(B) = \det(A)$

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# Outline

## 1 Square Matrices

- Introduction
- The Inverse
- Solution to  $A\mathbf{x} = \mathbf{y}$
- Algorithm for the Inverse of a Matrix

## 2 Determinants

- Introduction
- Complexity Increases
- Reducing the Complexity
- Some Consequences of the definition
- **Special Determinants**



# Therefore

## Theorem

The determinant of an upper or lower triangular matrix is equal to the product of the entries on the main diagonal.



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## Proof

- Suppose  $A$  is upper triangular and that none of the entries on the main diagonal is 0.
- This means all the entries beneath the main diagonal are zero.
- Using Proposition 3, we can convert it into a diagonal matrix.
- Then, by property 1

$$\triangleright \det(A_{\text{diag}}) = \left[ \prod_{i=1}^n a_{ii} \right] \det(I) = \prod_{i=1}^n a_{ii}$$





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## Remark

### Question

This is the property we use to compute determinants!!! How?



## Example

We have

$$\begin{pmatrix} 2 & 1 \\ 3 & -4 \end{pmatrix}$$

First, we have

$$r_1 = (2, 1) = 2 \left( 2, \frac{1}{2} \right)$$

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## Further

We have by proposition 3

$$\det(A) = 2 \det \begin{bmatrix} 1 & \frac{1}{2} \\ 0 & -\frac{11}{2} \end{bmatrix}$$

Using Property 1

$$\det(A) = 2 \left( -\frac{11}{2} \right) \det \begin{bmatrix} 1 & \frac{1}{2} \\ 0 & 1 \end{bmatrix}$$

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## Property 4

The determinant of  $A$  is the same as that of its transpose  $A^T$ .

### Proof

- Hint: we do an elementary row operation on  $A$ . Then,  
 $(EA)^T = A^T E^T$



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### Property 5

If  $A$  and  $B$  are square matrices of the same size, then

$$\det(AB) = \det(A) \det(B)$$

Therefore:

If  $A$  is invertible:

$$\begin{aligned}\det(AA^{-1}) &= \det(A) \det(A^{-1}) \\ &= \det(I) \\ &= 1\end{aligned}$$

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## Definition

- If the (square) matrix  $A$  is invertible, then  $A$  is said to be non-singular.
- Otherwise,  $A$  is singular.

