

# Matrix Inverses

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## Solving multiple systems

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$$\begin{array}{l} \left( \begin{array}{cc|cc} 1 & 2 & 3 & 1 \\ 2 & 5 & 4 & 0 \end{array} \right) \xrightarrow{R_2 - 2R_1} \left( \begin{array}{cc|cc} 1 & 2 & 3 & 1 \\ 0 & 1 & -2 & -2 \end{array} \right) \\ \xrightarrow{R_1 - 2R_2} \left( \begin{array}{cc|cc} 1 & 0 & 7 & 5 \\ 0 & 1 & -2 & -2 \end{array} \right) \end{array}$$

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The first augmented column deals with the first system and the reduced echelon form above tells us that its solution is  $(7, -2)$ . The second augmented column relates to the second system and gives the solution  $(5, -2)$ .

This observation allows us to solve matrix equations: For example, suppose  $A$  and  $B$  are matrices and we need to solve for a matrix  $X$  that satisfies  $AX = B$ . Then each column of  $AX$  must equal the corresponding column of  $B$ ,

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$$\text{Solve: } \begin{pmatrix} 1 & 2 & 3 \\ 1 & 3 & -2 \\ 2 & 4 & 8 \end{pmatrix} X = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

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Start with the triply-augmented matrix  $(A | I)$  and begin applying EROs:

$$\left( \begin{array}{ccc|ccc} 1 & 2 & 3 & 1 & 0 & 0 \\ 1 & 3 & -2 & 0 & 1 & 0 \\ 2 & 4 & 8 & 0 & 0 & 1 \end{array} \right) \xrightarrow{\substack{R_2 - R_1 \\ R_3 - 2R_1}} \left( \begin{array}{ccc|ccc} 1 & 2 & 3 & 1 & 0 & 0 \\ 0 & 1 & -5 & -1 & 1 & 0 \\ 0 & 0 & 2 & -2 & 0 & 1 \end{array} \right)$$

Now take  $1/2$  times row 3 and continue

$$\left( \begin{array}{ccc|ccc} 1 & 2 & 3 & 1 & 0 & 0 \\ 0 & 1 & -5 & -1 & 1 & 0 \\ 0 & 0 & 1 & -1 & 0 & 1/2 \end{array} \right) \xrightarrow[\begin{array}{l} R_2+5R_3 \\ R_1-3R_3 \end{array}]{\phantom{\rightarrow}} \left( \begin{array}{ccc|ccc} 1 & 2 & 0 & 4 & 0 & -3/2 \\ 0 & 1 & 0 & -6 & 1 & 5/2 \\ 0 & 0 & 1 & -1 & 0 & 1/2 \end{array} \right)$$

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Finally,

$$\xrightarrow{R_1-2R_2} \left( \begin{array}{ccc|ccc} 1 & 0 & 0 & 16 & -2 & -13/2 \\ 0 & 1 & 0 & -6 & 1 & 5/2 \\ 0 & 0 & 1 & -1 & 0 & 1/2 \end{array} \right)$$

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This tells us that the columns of  $X$  are

$$\begin{pmatrix} 16 \\ -6 \\ -1 \end{pmatrix}, \begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix} \text{ and } \begin{pmatrix} -13/2 \\ 5/2 \\ 1/2 \end{pmatrix} \text{ so } X = \begin{pmatrix} 16 & -2 & -13/2 \\ -6 & 1 & 5/2 \\ -1 & 0 & 1/2 \end{pmatrix}$$



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$$\left( A \mid I \right) \xrightarrow{\text{Some EROs}} \left( I \mid A^{-1} \right)$$

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If it turns out that you cannot get the identity in the left half (i.e., one of the columns does not have a leading 1), then  $A$  is not invertible.

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Examples

$$E_1 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}, \quad E_2 = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad E_3 = \begin{pmatrix} 1 & -3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

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If  $A$  is any matrix and  $E$  is an elementary matrix, then  $EA$  is the result of applying the corresponding ERO to  $A$ .

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Example, using  $E_3$  from above

$$E_3 \begin{pmatrix} 1 & 3 & 2 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix}$$

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$$E_1^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}, \quad E_2^{-1} = \begin{pmatrix} 1/2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad E_3^{-1} = \begin{pmatrix} 1 & 3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

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$$E_3(E_2(E_1A)) = I \quad \text{means} \quad (E_3E_2E_1)A = I, \quad \text{so} \quad A^{-1} = E_3E_2E_1$$

From  $A^{-1} = E_3E_2E_1$  we also get

$$A = (A^{-1})^{-1} = (E_3E_2E_1)^{-1} = E_1^{-1}E_2^{-1}E_3^{-1}$$



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If we let  $M = E_m \cdots E_2E_1$  then this is the same as

$$M \left( A \mid I \right) = \left( MA \mid MI \right) = \left( I \mid M \right)$$

This last formula says two things: one is that  $MA = I$ , but also it says that  $M$  is the solution of  $AX = I$  and so  $AM = I$ . Thus we really do get the inverse because we get  $I$  with either order of multiplication.

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- 4.  $A\mathbf{x} = \mathbf{0}$  has a unique solution.*

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*Moreover, in this case  $A\mathbf{x} = \mathbf{b}$  always has a unique solution  $\mathbf{x} = A^{-1}\mathbf{b}$ .*