



## Solving Matrix-Vector Equations

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$$A\vec{x} = \begin{pmatrix} 1 & -1 \\ 2 & 1 \\ 4 & -2 \end{pmatrix} \times \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$



$$= \begin{pmatrix} 1 \times 1 & + & (-1) \times 2 \\ 2 \times 1 & + & 1 \times 2 \\ 4 \times 1 & + & (-2) \times 2 \end{pmatrix}$$



$$= 1 \times \begin{pmatrix} 1 \\ 2 \\ 4 \end{pmatrix} + 2 \times \begin{pmatrix} -1 \\ 1 \\ -2 \end{pmatrix}$$



```
> A%*%x
[,1]
[1,] -1
[2,] 4
[3,] 0
```

```
> A[, 1]*x[1] + A[,2]*x[2]
[1] -1 4 0
```



$$A\vec{x} = \vec{b}$$

$$\begin{pmatrix} 4 & -2 \\ -3 & 2 \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} -1 \\ 1 \end{pmatrix}$$

$$x_1 \times \begin{pmatrix} 4 \\ -3 \end{pmatrix} + x_2 \times \begin{pmatrix} -2 \\ 2 \end{pmatrix} = \begin{pmatrix} -1 \\ 1 \end{pmatrix}$$



## Example of a Matrix-Vector Equation

Teams	Johns Hopkins	F & M	Gettysburg	Dickinson	McDaniel
Johns Hopkins	_	Loss, 12 - 14	Win 49-35	Win 49-0	Win 49-7
F & M	Win, 14 - 12	-	Loss, 31-38	Win 36-28	Win 35-10
Gettsyburg	Loss 35-49	Win, 38-31	-	Loss 13-23	Win 35-3
Dickinson	Loss 0-49	Loss 28-36	Win 23-13	-	Win 38-31
McDaniel	Loss 7-49	Loss 10-35	Loss 3-35	Loss 31-38	-



### Example of a Matrix-Vector Equation



## Example of a Matrix-Vector Equation





## Let's practice!





## Matrix-Vector Equations - Some Theory

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## A Matrix-Vector Equation Without a Solution

Inconsistent

$$\begin{pmatrix} 1 & -1 \\ 0 & 0 \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} -1 \\ 2 \end{pmatrix}$$
$$x_1 - x_2 = -1$$
$$0 = 2$$



## A Matrix-Vector Equation with Infinitely-Many Solutions

Consistent (but infinitely-many solutions)

$$\left(\begin{array}{cc} 1 & -1 \\ 0 & 0 \end{array}\right) \times \left(\begin{array}{c} x_1 \\ x_2 \end{array}\right) = \left(\begin{array}{c} -1 \\ 0 \end{array}\right)$$

$$x_1 - x_2 = -1$$
$$0 = 0$$

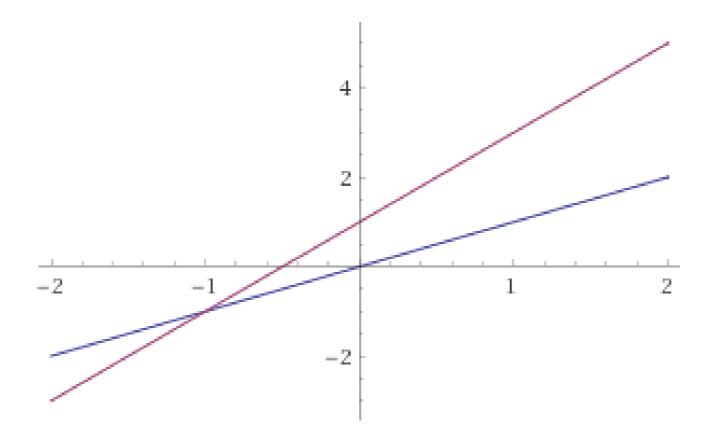
## A Matrix-Vector Equation with a Unique Solution

Consistent (unique solution)

$$\left(\begin{array}{cc} 1 & -1 \\ 1 & 0 \end{array}\right) \times \left(\begin{array}{c} x_1 \\ x_2 \end{array}\right) = \left(\begin{array}{c} -1 \\ 0 \end{array}\right)$$

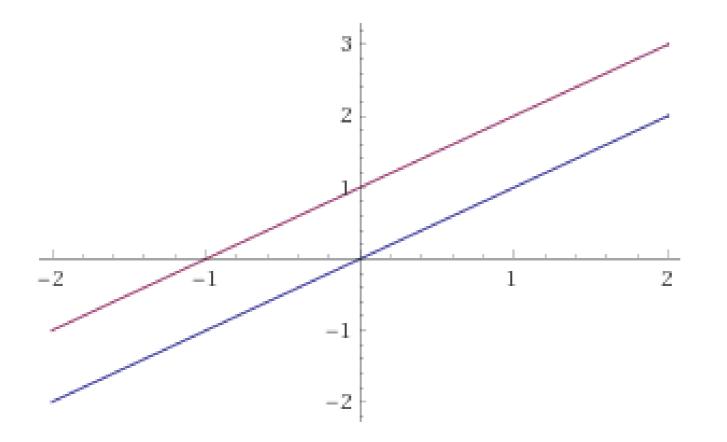
$$x_1 - x_2 = -1$$
$$x_1 = 0$$

## Properties of Solutions to Matrix-Vector Equations - Exactly One Solution



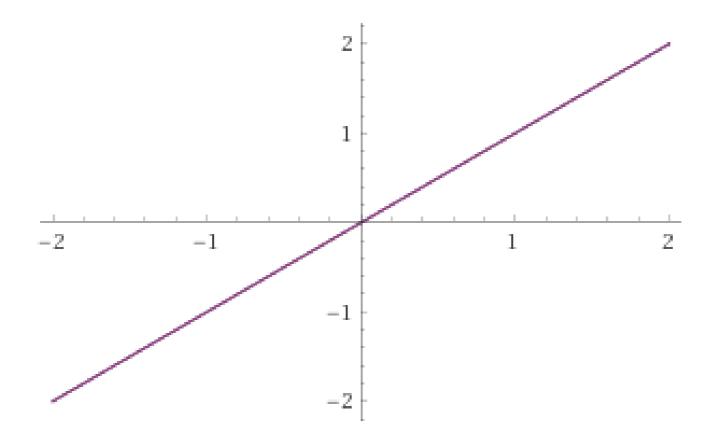


## Properties of Solutions to Matrix-Vector Equations - No Solutions





## Properties of Solutions to Matrix-Vector Equations - Infinitely-Many Solutions



## Properties to Ensure A Unique Solution to $A\vec{x}=\vec{b}$

If A is an n by n square matrix, then the following conditions are equivalent and imply a unique solution to

$$A\vec{x} = \vec{b}$$
:

- The matrix *A* has an inverse (is *invertible*)
- The *determinant* of *A* is nonzero
- The rows and columns of A form a *basis* for the set of all vectors with n elements



## Properties to Ensure A Unique Solution to $A\vec{x}=\vec{b}$

```
A
[,1] [,2]
[1,] 1 -2
[2,] 0 4
```

• Computing the Inverse of *A* (if it Exists)

```
solve(A)
[,1] [,2]
[1,] 1 0.50
[2,] 0 0.25
```

ullet Computing the Determinant of A

```
det(A)
[1] 4
```





## Let's practice!





## Solving Matrix-Vector Equations

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$$5x = 7$$

$$\frac{1}{5}5x = \frac{1}{5}7$$

$$1x = \frac{7}{5}$$

$$x = \frac{7}{5}$$



$$A\vec{x} = \vec{b}$$

$$A^{-1}A\vec{x} = A^{-1}\vec{b}$$

$$I\vec{x} = A^{-1}\vec{b}$$

$$\vec{x} = A^{-1}\vec{b}$$



```
A
[,1] [,2]
[1,] 1 -2
[2,] 0 4

b
[1] 1 -2
```

Solving  $A\vec{x} = \vec{b}$  using  $\vec{x} = A^{-1}\vec{b}$ :

```
x <- solve(A)%*%b
print(x)
    [,1]
[1,] 0.0
[2,] -0.5</pre>
```



```
x <- solve(A)%*%b
print(x)
    [,1]
[1,] 0.0
[2,] -0.5</pre>
```

Checking your solution by plugging in the solution  $\vec{x}$ :

```
A%*%x
[,1]
[1,] 1
[2,] -2
```

Which is equal to the given  $\vec{b}$ :

```
print(b)
[1] 1 -2
```



## Additional Conditions for Unique Solutions

$$A\vec{x} = \vec{0}$$

$$A^{-1}A\vec{x} = A^{-1}\vec{0}$$

$$I\vec{x} = A^{-1}\vec{0}$$

$$\vec{x} = A^{-1}\vec{0}$$

$$\vec{x} = \vec{0}$$

Thus, the only solution to the *homogeneous* equation  $A\vec{x} = \vec{0}$  is the *trivial* solution  $\vec{x} = \vec{0}$ .



## Additional Conditions for Unique Solutions

```
> solve(A)%*%b
[,1]
[1,] 0
[2,] 0
```



## Conditions for a Unique Solution to Matrix-Vector Equations

If A is an n by n square matrix, then the following conditions are equivalent and imply a unique solution to

$$A\vec{x} = \vec{b}$$
:

- The matrix A has an inverse (is *invertible*)
- The *determinant* of *A* is nonzero
- The rows and columns of A form a basis for the set of all vectors with n elements
- The homogeneous equation  $A\vec{x}=\vec{0}$  has just the trivial  $(\vec{x}=0)$  solution





## Let's Practice!





# Other Considerations for Matrix-Vector Equations

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## More Equations than Unknowns

$$2x_1 + 3x_2 = 7$$
$$-x_1 + 4x_2 = 1$$
$$x_1 + 7x_2 = 0$$

$$\begin{pmatrix} 2 & 3 \\ -1 & 4 \\ 1 & 7 \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 2 \\ -1 \\ 1 \end{pmatrix} + x_2 \times \begin{pmatrix} 3 \\ 4 \\ 7 \end{pmatrix} = \begin{pmatrix} 7 \\ 1 \\ 0 \end{pmatrix}$$



## More Equations than Unknowns

$$2x_1 + 3x_2 = 7$$
$$-x_1 + 4x_2 = 1$$
$$x_1 + 7x_2 = 0$$

$$\begin{pmatrix} 2 & 3 \\ -1 & 4 \\ 1 & 7 \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} =$$

$$x_1 \times \begin{pmatrix} 2 \\ -1 \\ 1 \end{pmatrix} + x_2 \times \begin{pmatrix} 3 \\ 4 \\ 7 \end{pmatrix} = \begin{pmatrix} 7 \\ 1 \\ 0 \end{pmatrix}$$



### Fewer Equations than Unknowns

$$x_1 - x_2 + 4x_3 = 0$$
$$2x_1 + 5x_2 + 7x_3 = 1$$

$$\begin{pmatrix} 1 & -1 & 4 \\ 2 & 5 & 7 \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} =$$

$$x_1 \times \begin{pmatrix} 1 \\ 2 \end{pmatrix} + x_2 \times \begin{pmatrix} -1 \\ 5 \end{pmatrix} + x_3 \times \begin{pmatrix} 4 \\ 7 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$



## Some Options for Non-Square Matrices

- Row Reduction (By Hand, Difficult for Big Problems)
- Least Squares (If More Rows Than Columns Used in Linear Regression)
- Singular Value Decomposition (If More Columns Than Rows Used in Principal Component Analysis)
- Generalized or Pseudo-Inverse



#### Moore-Penrose Generalized Inverse

[2,] 0.0000000 0.09090909 0.09090909

```
library (MASS)

A

[,1] [,2]

[1,] 2 3

[2,] -1 4

[3,] 1 7

ginv(A)

[,1] [,2] [,3]

[1,] 0.3333333 -0.30303030 0.03030303
```



#### Moore-Penrose Generalized Inverse

```
[1,1] [,2]
[1,] 2 3
[2,] -1 4
[3,] 1 7

b
[1] 1 7 8
```

```
{r} <- ginv(A)%*%b A%*%x [,1] [1,] 1 [2,] 7 [3,] 8 {{2}}
```





## **Let's Practice**