

# ECON2125/4021/8013

## Lecture 9

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Semester 1, 2015

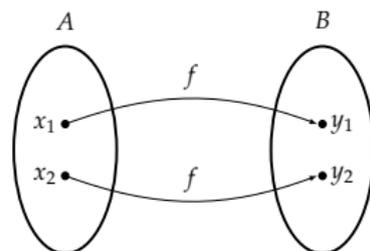
# Announcements

- Preliminary midterm exam date: April 23rd
- Solved exercises up on GitHub
- Extended office hours for tutors
  - 4:00-6:00pm on Friday for Guanlong
  - 3:00-5:00pm on Friday for Qingyin
- Proofs / logic / sets reference, if you want one
  - Simon and Blume, appendix A1
  - Sydsaeter and Hammond, Chapter 1
- Linear algebra reference, if you want one
  - “Linear Algebra” by David Lay (expensive but good)

## Reminder I

Suppose we want to find the  $x$  that solves  $f(x) = y$

The ideal case is when  $f$  is a bijection



Equivalent:

- $f$  is a bijection
- each  $y \in B$  has a unique preimage
- $f(x) = y$  has a unique solution  $x$  for each  $y$

## Reminder II

Let  $T$  be a linear function from  $\mathbb{R}^N$  to  $\mathbb{R}^N$

We saw that in this case all of the following are equivalent:

1.  $T$  is a bijection
2.  $T$  is onto
3.  $T$  is one-to-one
4.  $\ker(T) = \{\mathbf{0}\}$
5.  $V := \{T\mathbf{e}_1, \dots, T\mathbf{e}_N\}$  is linearly independent

We then say that  $T$  is nonsingular (= linear bijection)

# Linear Equations

Let's look at solving linear equations such as  $\mathbf{Ax} = \mathbf{b}$

We start with the “best” case:

$$\text{number of equations} = \text{number of unknowns}$$

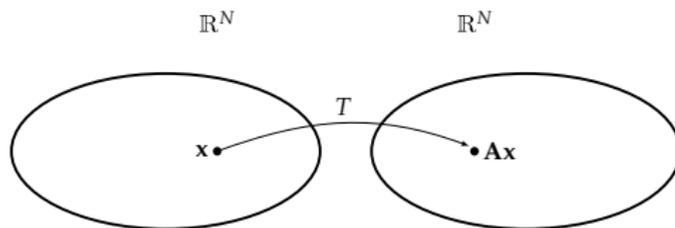
Thus,

- Take  $N \times N$  matrix  $\mathbf{A}$  and  $N \times 1$  vector  $\mathbf{b}$  as given
- Search for an  $N \times 1$  solution  $\mathbf{x}$

But does such a solution exist? If so is it unique?

The best way to think about this is to consider the corresponding linear map

$$T: \mathbb{R}^N \rightarrow \mathbb{R}^N, \quad T\mathbf{x} = \mathbf{A}\mathbf{x}$$



Equivalent:

1.  $\mathbf{Ax} = \mathbf{b}$  has a unique solution  $\mathbf{x}$  for any given  $\mathbf{b}$
2.  $T\mathbf{x} = \mathbf{b}$  has a unique solution  $\mathbf{x}$  for any given  $\mathbf{b}$
3.  $T$  is a bijection

We already have conditions for linear maps to be bijections

Just need to translate these into the matrix setting

Recall that  $T$  called nonsingular if  $T$  is a linear bijection

We say that  $\mathbf{A}$  is **nonsingular** if  $T$  is nonsingular

Equivalent:

- $\mathbf{x} \mapsto \mathbf{Ax}$  is a bijection from  $\mathbb{R}^N$  to  $\mathbb{R}^N$

We now list equivalent conditions for nonsingularity

Let  $\mathbf{A}$  be an  $N \times N$  matrix

**Fact.** All of the following conditions are equivalent

1.  $\mathbf{A}$  is nonsingular
2. The columns of  $\mathbf{A}$  are linearly independent
3.  $\text{rank}(\mathbf{A}) = N$
4.  $\text{span}(\mathbf{A}) = \mathbb{R}^N$
5. If  $\mathbf{Ax} = \mathbf{Ay}$ , then  $\mathbf{x} = \mathbf{y}$
6. If  $\mathbf{Ax} = \mathbf{0}$ , then  $\mathbf{x} = \mathbf{0}$
7. For each  $\mathbf{b} \in \mathbb{R}^N$ , the equation  $\mathbf{Ax} = \mathbf{b}$  has a solution
8. For each  $\mathbf{b} \in \mathbb{R}^N$ , the equation  $\mathbf{Ax} = \mathbf{b}$  has a unique solution

All equivalent ways of saying that  $T\mathbf{x} = \mathbf{Ax}$  is a bijection!

**Example.** For condition 5 the equivalence is

if  $\mathbf{Ax} = \mathbf{Ay}$ , then  $\mathbf{x} = \mathbf{y}$

$\iff$  if  $T\mathbf{x} = T\mathbf{y}$ , then  $\mathbf{x} = \mathbf{y}$

$\iff$   $T$  is one-to-one

Since  $T$  is a linear map from  $\mathbb{R}^N$  to  $\mathbb{R}^N$ ,

$\iff$   $T$  is a bijection

**Example.** For condition 6 the equivalence is

if  $\mathbf{Ax} = \mathbf{0}$ , then  $\mathbf{x} = \mathbf{0}$

$$\iff \{\mathbf{x} : \mathbf{Ax} = \mathbf{0}\} = \{\mathbf{0}\}$$

$$\iff \{\mathbf{x} : T\mathbf{x} = \mathbf{0}\} = \{\mathbf{0}\}$$

$$\iff \ker(T) = \{\mathbf{0}\}$$

Since  $T$  is a linear map from  $\mathbb{R}^N$  to  $\mathbb{R}^N$ ,

$$\iff T \text{ is a bijection}$$

**Example.** For condition 7 the equivalence is

for each  $\mathbf{b} \in \mathbb{R}^N$ , the equation  $\mathbf{Ax} = \mathbf{b}$  has a solution

$$\iff \text{every } \mathbf{b} \in \mathbb{R}^N \text{ has an } \mathbf{x} \text{ such that } \mathbf{Ax} = \mathbf{b}$$

$$\iff \text{every } \mathbf{b} \in \mathbb{R}^N \text{ has an } \mathbf{x} \text{ such that } T\mathbf{x} = \mathbf{b}$$

$$\iff T \text{ is onto}$$

Since  $T$  is a linear map from  $\mathbb{R}^N$  to  $\mathbb{R}^N$ ,

$$\iff T \text{ is a bijection}$$

Now consider condition 2:

The columns of  $\mathbf{A}$  are linearly independent

Let  $\mathbf{e}_n$  be the  $n$ -th canonical basis vector in  $\mathbb{R}^N$

Observe that  $\mathbf{A}\mathbf{e}_n = \text{col}_n(\mathbf{A})$

$$\therefore T\mathbf{e}_n = \text{col}_n(\mathbf{A})$$

$$\therefore V := \{T\mathbf{e}_1, \dots, T\mathbf{e}_N\} = \text{columns of } \mathbf{A}$$

And  $V$  is linearly independent if and only if  $T$  is a bijection

**Example.** Consider a one good linear market system

$$q = a - bp \quad (\text{demand})$$

$$q = c + dp \quad (\text{supply})$$

Treating  $q$  and  $p$  as the unknowns, let's write in matrix form as

$$\begin{pmatrix} 1 & b \\ 1 & -d \end{pmatrix} \begin{pmatrix} q \\ p \end{pmatrix} = \begin{pmatrix} a \\ c \end{pmatrix}$$

A unique solution exists whenever the columns are linearly independent

- means that  $(b, -d)$  is not a scalar multiple of  $\mathbf{1}$
- means that  $b \neq -d$

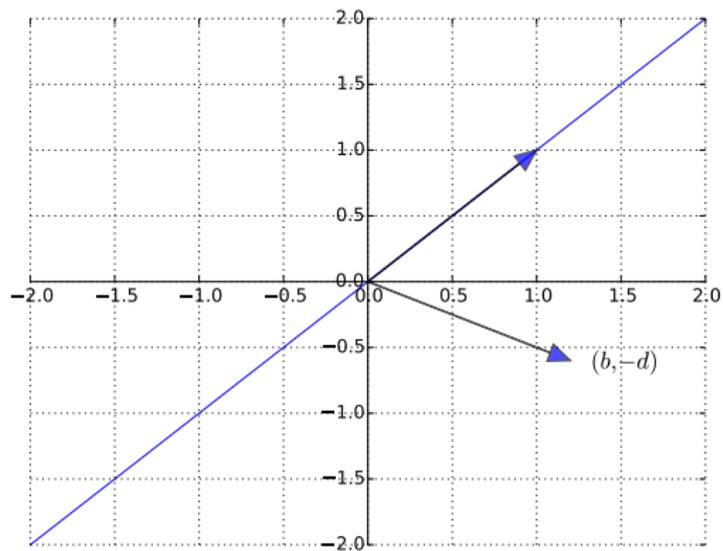


Figure :  $(b, -d)$  is not a scalar multiple of  $\mathbf{1}$

**Example.** Recall when we try to solve the system  $\mathbf{Ax} = \mathbf{b}$  of this form

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```
In [1]: import numpy as np
```

```
In [2]: from scipy.linalg import solve
```

```
In [3]: A = [[0, 2, 4],  
...:        [1, 4, 8],  
...:        [0, 3, 6]]
```

```
In [4]: b = (1, 2, 0)
```

```
In [5]: A, b = np.asarray(A), np.asarray(b)
```

```
In [6]: solve(A, b)
```

---

This is the output that we got

```
LinAlgError          Traceback (most recent call last)
<ipython-input-8-4fb5f41eaf7c> in <module>()
----> 1 solve(A, b)
/home/john/anaconda/lib/python2.7/site-packages/scipy/linalg
    97         return x
    98     if info > 0:
---> 99         raise LinAlgError("singular matrix")
    100     raise ValueError('illegal value in %d-th argument')
LinAlgError: singular matrix
```

The problem is that  $\mathbf{A}$  is singular (not nonsingular)

- In particular,  $\text{col}_3(\mathbf{A}) = 2 \text{col}_2(\mathbf{A})$

# Inverse Matrices

Given square matrix  $\mathbf{A}$ , suppose  $\exists$  square matrix  $\mathbf{B}$  such that

$$\mathbf{AB} = \mathbf{BA} = \mathbf{I}$$

Then

- $\mathbf{B}$  is called the **inverse** of  $\mathbf{A}$ , and written  $\mathbf{A}^{-1}$
- $\mathbf{A}$  is called **invertible**

**Fact.** A square matrix  $\mathbf{A}$  is nonsingular if and only if it is invertible

Remark

- $\mathbf{A}^{-1}$  is just the matrix corresponding to the linear map  $T^{-1}$

**Fact.** Given nonsingular  $N \times N$  matrix  $\mathbf{A}$  and  $\mathbf{b} \in \mathbb{R}^N$ , the unique solution to  $\mathbf{Ax} = \mathbf{b}$  is given by

$$\mathbf{x}_b := \mathbf{A}^{-1}\mathbf{b}$$

Proof: Since  $\mathbf{A}$  is nonsingular we already know any solution is unique

- $T$  is a bijection, and hence one-to-one
- if  $\mathbf{Ax} = \mathbf{Ay} = \mathbf{b}$  then  $\mathbf{x} = \mathbf{y}$

To show that  $\mathbf{x}_b$  is indeed a solution we need to show that  $\mathbf{Ax}_b = \mathbf{b}$

To see this, observe that

$$\mathbf{Ax}_b = \mathbf{AA}^{-1}\mathbf{b} = \mathbf{Ib} = \mathbf{b}$$

**Example.** Recall the one good linear market system

$$\begin{aligned} q &= a - bp \\ q &= c + dp \end{aligned} \iff \begin{pmatrix} 1 & b \\ 1 & -d \end{pmatrix} \begin{pmatrix} q \\ p \end{pmatrix} = \begin{pmatrix} a \\ c \end{pmatrix}$$

Suppose that  $a = 5$ ,  $b = 2$ ,  $c = 1$ ,  $d = 1.5$

The matrix system is  $\mathbf{Ax} = \mathbf{b}$  where

$$\mathbf{A} := \begin{pmatrix} 1 & 2 \\ 1 & -1.5 \end{pmatrix}, \mathbf{x} := \begin{pmatrix} q \\ p \end{pmatrix}, \mathbf{b} := \begin{pmatrix} 5 \\ 1 \end{pmatrix}$$

Since  $b \neq -d$  we can solve for the unique solution

Easy by hand but let's try on the computer

---

```
In [1]: import numpy as np
In [2]: from scipy.linalg import inv

In [3]: A = [[1, 2],
...:        [1, -1.5]]

In [4]: b = [5, 1]

In [5]: q, p = np.dot(inv(A), b)  #  $A^{-1} b$ 

In [6]: q
Out[6]: 2.7142857142857144
In [7]: p
Out[7]: 1.1428571428571428
```

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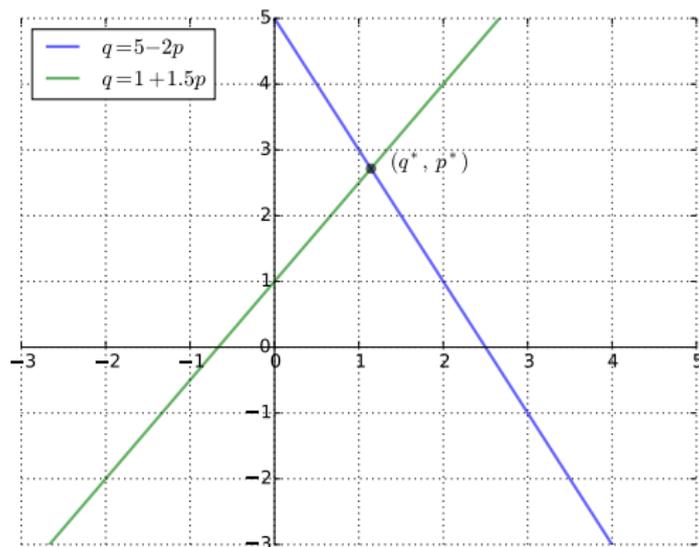


Figure : Equilibrium  $(p^*, q^*)$  in the one good case

**Fact.** In the  $2 \times 2$  case, the inverse has the form

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

**Example.**

$$\mathbf{A} = \begin{pmatrix} 1 & 2 \\ 1 & -1.5 \end{pmatrix} \implies \mathbf{A}^{-1} = \frac{1}{-3.5} \begin{pmatrix} -1.5 & -2 \\ -1 & 1 \end{pmatrix}$$

**Example.** Consider the  $N$  good linear demand system

$$q_n = \sum_{k=1}^N a_{nk} p_k + b_n, \quad n = 1, \dots, N \quad (1)$$

Task: take quantities  $q_1, \dots, q_N$  as given and find corresponding prices  $p_1, \dots, p_N$  — the “inverse demand curves”

We can write (1) as

$$\mathbf{q} = \mathbf{A}\mathbf{p} + \mathbf{b}$$

where vectors are  $N$ -vectors and  $\mathbf{A}$  is  $N \times N$

If the columns of  $\mathbf{A}$  are linearly independent then a unique solution exists for each fixed  $\mathbf{q}$  and  $\mathbf{b}$ , and is given by

$$\mathbf{p} = \mathbf{A}^{-1}(\mathbf{q} - \mathbf{b})$$

## Left and Right Inverses

Given square matrix  $\mathbf{A}$ , a matrix  $\mathbf{B}$  is called

- a **left inverse** of  $\mathbf{A}$  if  $\mathbf{BA} = \mathbf{I}$
- a **right inverse** of  $\mathbf{A}$  if  $\mathbf{AB} = \mathbf{I}$

By definition, a matrix that is both an left inverse and a right inverse is an inverse

**Fact.** If square matrix  $\mathbf{B}$  is either a left or right inverse for  $\mathbf{A}$ , then  $\mathbf{A}$  is nonsingular and  $\mathbf{A}^{-1} = \mathbf{B}$

In other words, for square matrices,

$$\text{left inverse} \iff \text{right inverse} \iff \text{inverse}$$

## Rules for Inverses

**Fact.** If  $\mathbf{A}$  is nonsingular and  $\alpha \neq 0$ , then

1.  $\mathbf{A}^{-1}$  is nonsingular and  $(\mathbf{A}^{-1})^{-1} = \mathbf{A}$
2.  $\alpha\mathbf{A}$  is nonsingular and  $(\alpha\mathbf{A})^{-1} = \alpha^{-1}\mathbf{A}^{-1}$

Proof of part 2:

It suffices to show that  $\alpha^{-1}\mathbf{A}^{-1}$  is the right inverse of  $\alpha\mathbf{A}$

This is true because

$$\alpha\mathbf{A}\alpha^{-1}\mathbf{A}^{-1} = \alpha\alpha^{-1}\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$$

**Fact.** If  $\mathbf{A}$  and  $\mathbf{B}$  are  $N \times N$  and nonsingular then

1.  $\mathbf{AB}$  is also nonsingular
2.  $(\mathbf{AB})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$

Proof I: Let  $T$  and  $U$  be the linear maps corresponding to  $\mathbf{A}$  and  $\mathbf{B}$

Recall that

- $T \circ U$  is the linear map corresponding to  $\mathbf{AB}$
- Compositions of linear maps are linear
- Compositions of bijections are bijections

Hence  $T \circ U$  is a linear bijection with  $(T \circ U)^{-1} = U^{-1} \circ T^{-1}$

That is,  $\mathbf{AB}$  is nonsingular with inverse  $\mathbf{B}^{-1}\mathbf{A}^{-1}$

Proof II:

A different proof that  $\mathbf{AB}$  is nonsingular with inverse  $\mathbf{B}^{-1}\mathbf{A}^{-1}$

Suffices to show that  $\mathbf{B}^{-1}\mathbf{A}^{-1}$  is the right inverse of  $\mathbf{AB}$

To see this, observe that

$$\mathbf{ABB}^{-1}\mathbf{A}^{-1} = \mathbf{AA}^{-1} = \mathbf{I}$$

Hence  $\mathbf{B}^{-1}\mathbf{A}^{-1}$  is a right inverse as claimed

## When the Conditions Fail

Suppose as before we have

- an  $N \times N$  matrix  $\mathbf{A}$
- an  $N \times 1$  vector  $\mathbf{b}$

We seek a solution  $\mathbf{x}$  to the equation  $\mathbf{Ax} = \mathbf{b}$

What if  $\mathbf{A}$  is singular?

Then  $T\mathbf{x} = \mathbf{Ax}$  is not a bijection, and in fact

- $T$  cannot be onto (otherwise it's a bijection)
- $T$  cannot be one-to-one (otherwise it's a bijection)

Hence neither existence nor uniqueness is guaranteed

**Example.** The matrix  $\mathbf{A}$  with columns

$$\mathbf{a}_1 := \begin{pmatrix} 3 \\ 4 \\ 2 \end{pmatrix}, \quad \mathbf{a}_2 := \begin{pmatrix} 3 \\ -4 \\ 1 \end{pmatrix} \quad \text{and} \quad \mathbf{a}_3 := \begin{pmatrix} -3 \\ 4 \\ -1 \end{pmatrix}$$

is singular ( $\mathbf{a}_3 = -\mathbf{a}_2$ )

Its column space  $\text{span}(\mathbf{A})$  is just a plane in  $\mathbb{R}^3$

Recall  $\mathbf{b} \in \text{span}(\mathbf{A})$

$$\iff \exists x_1, \dots, x_N \text{ such that } \sum_{k=1}^N x_k \text{col}_k(\mathbf{A}) = \mathbf{b}$$

$$\iff \exists \mathbf{x} \text{ such that } \mathbf{Ax} = \mathbf{b}$$

Thus if  $\mathbf{b}$  is not in this plane then  $\mathbf{Ax} = \mathbf{b}$  has no solution

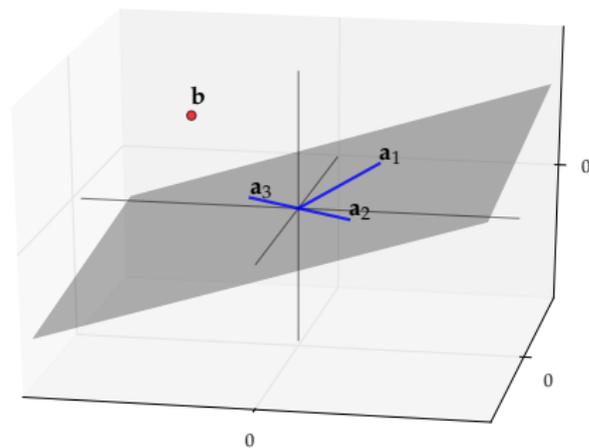


Figure : The vector  $\mathbf{b}$  is not in  $\text{span}(\mathbf{A})$

When  $\mathbf{A}$  is  $N \times N$  and singular how rare is scenario  $\mathbf{b} \in \text{span}(\mathbf{A})$ ?

Answer: In a sense, very rare

We know that  $\dim(\text{span}(\mathbf{A})) < N$

Such sets are always “very small” subset of  $\mathbb{R}^N$  in terms of “volume”

- A  $K < N$  dimensional subspace has “measure zero” in  $\mathbb{R}^N$
- A “randomly chosen”  $\mathbf{b}$  has zero probability of being in such a set

**Example.** Consider the case where  $N = 3$  and  $K = 2$

A two-dimensional linear subspace is a 2D plane in  $\mathbb{R}^3$

This set has no volume because planes have no “thickness”

All this means that if  $\mathbf{A}$  is singular then existence of a solution to  $\mathbf{Ax} = \mathbf{b}$  typically fails

In fact the problem is worse — uniqueness fails as well

**Fact.** If  $\mathbf{A}$  is a singular matrix and  $\mathbf{Ax} = \mathbf{b}$  has a solution then it has an infinity (in fact a continuum) of solutions

Proof: Let  $\mathbf{A}$  be singular and let  $\mathbf{x}$  be a solution

Since  $\mathbf{A}$  is singular there exists a nonzero  $\mathbf{y}$  with  $\mathbf{Ay} = \mathbf{0}$

But then  $\alpha\mathbf{y} + \mathbf{x}$  is also a solution for any  $\alpha \in \mathbb{R}$  because

$$\mathbf{A}(\alpha\mathbf{y} + \mathbf{x}) = \alpha\mathbf{Ay} + \mathbf{Ax} = \mathbf{Ax} = \mathbf{b}$$

# Determinants

Let  $S(N)$  be set of all bijections from  $\{1, \dots, N\}$  to itself

For  $\pi \in S(N)$  we define the **signature** of  $\pi$  as

$$\text{sgn}(\pi) := \prod_{m < n} \frac{\pi(m) - \pi(n)}{m - n}$$

The **determinant** of  $N \times N$  matrix  $\mathbf{A}$  is then given as

$$\det(\mathbf{A}) := \sum_{\pi \in S(N)} \text{sgn}(\pi) \prod_{n=1}^N a_{\pi(n)n}$$

- You don't need to understand or remember this for our course

**Fact.** In the  $N = 2$  case this definition reduces to

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

- Remark: But you do need to remember this  $2 \times 2$  case

Example

$$\det \begin{pmatrix} 2 & 0 \\ 7 & -1 \end{pmatrix} = (2 \times -1) - (7 \times 0) = -2$$

## Important facts concerning the determinant

**Fact.** If  $\mathbf{I}$  is the  $N \times N$  identity,  $\mathbf{A}$  and  $\mathbf{B}$  are  $N \times N$  matrices and  $\alpha \in \mathbb{R}$ , then

1.  $\det(\mathbf{I}) = 1$
2.  $\mathbf{A}$  is nonsingular if and only if  $\det(\mathbf{A}) \neq 0$
3.  $\det(\mathbf{AB}) = \det(\mathbf{A}) \det(\mathbf{B})$
4.  $\det(\alpha \mathbf{A}) = \alpha^N \det(\mathbf{A})$
5.  $\det(\mathbf{A}^{-1}) = (\det(\mathbf{A}))^{-1}$

**Example.** Thus singularity in the  $2 \times 2$  case is equivalent to

$$\det(\mathbf{A}) = \det \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = a_{11}a_{22} - a_{12}a_{21} = 0$$

**Ex.** Let  $\mathbf{a}_i := \text{col}_i(\mathbf{A})$  and assume that  $a_{ij} \neq 0$  for each  $i, j$

Show the following are equivalent:

1.  $a_{11}a_{22} = a_{12}a_{21}$
2.  $\mathbf{a}_1 = \lambda \mathbf{a}_2$  for some  $\lambda \in \mathbb{R}$

---

```
In [1]: import numpy as np
```

```
In [2]: A = np.random.randn(2, 2)  # Random matrix
```

```
In [3]: A
```

```
Out[3]:
```

```
array([[ -0.70120551,  0.57088203],  
       [ 0.40757074, -0.72769741]])
```

```
In [4]: np.linalg.det(A)
```

```
Out[4]: 0.27759063032043652
```

```
In [5]: 1.0 / np.linalg.det(np.linalg.inv(A))
```

```
Out[5]: 0.27759063032043652
```

---

As an exercise, let's now show that any right inverse is an inverse

Fix square  $\mathbf{A}$  and suppose  $\mathbf{B}$  is a right inverse:

$$\mathbf{AB} = \mathbf{I} \quad (2)$$

Applying the determinant to both sides gives  $\det(\mathbf{A}) \det(\mathbf{B}) = 1$

Hence  $\mathbf{B}$  is nonsingular (why?) and we can

1. multiply (2) by  $\mathbf{B}$  to get  $\mathbf{BAB} = \mathbf{B}$
2. then postmultiply by  $\mathbf{B}^{-1}$  to get  $\mathbf{BA} = \mathbf{I}$

We see that  $\mathbf{B}$  is also left inverse, and therefore an inverse of  $\mathbf{A}$

**Ex.** Do the left inverse case

## Other Linear Equations

So far we have considered the nice  $N \times N$  case for equations

- number of equations = number of unknowns

We have to deal with other cases too

Underdetermined systems:

- eqs  $<$  unknowns

Overdetermined systems:

- eqs  $>$  unknowns

# Overdetermined Systems

Consider the system  $\mathbf{Ax} = \mathbf{b}$  where  $\mathbf{A}$  is  $N \times K$  and  $K < N$

- The elements of  $\mathbf{x}$  are the unknowns
- More equations than unknowns ( $N > K$ )

May not be able to find an  $\mathbf{x}$  that satisfies all  $N$  equations

Let's look at this in more detail...

Fix  $N \times K$  matrix  $\mathbf{A}$  with  $K < N$

Let  $T: \mathbb{R}^K \rightarrow \mathbb{R}^N$  be defined by  $T\mathbf{x} = \mathbf{A}\mathbf{x}$

We know these to be equivalent:

1. there exists an  $\mathbf{x} \in \mathbb{R}^K$  with  $\mathbf{A}\mathbf{x} = \mathbf{b}$
2.  $\mathbf{b}$  has a preimage under  $T$
3.  $\mathbf{b}$  is in  $\text{rng}(T)$
4.  $\mathbf{b}$  is in  $\text{span}(\mathbf{A})$

We also know  $T$  cannot be onto (maps small to big space)

Hence  $\mathbf{b} \in \text{span}(\mathbf{A})$  will not always hold

Given our assumption that  $K < N$ , how rare is the scenario  $\mathbf{b} \in \text{span}(\mathbf{A})$ ?

Answer: We talked about this before — it's very rare

We know that  $\dim(\text{rng}(T)) = \dim(\text{span}(\mathbf{A})) \leq K < N$

A  $K < N$  dimensional subspace has “measure zero” in  $\mathbb{R}^N$

So should we give up on solving  $\mathbf{Ax} = \mathbf{b}$  in the overdetermined case?

What's typically done is we try to find a best approximation

To define “best” we need a way of ranking approximations

The standard way is in terms of Euclidean norm

In particular, we search for the  $\mathbf{x}$  that solves

$$\min_{\mathbf{x} \in \mathbb{R}^k} \|\mathbf{Ax} - \mathbf{b}\|$$

Details later

## Underdetermined Systems

Now consider  $\mathbf{Ax} = \mathbf{b}$  when  $\mathbf{A}$  is  $N \times K$  and  $K > N$

Let  $T: \mathbb{R}^K \rightarrow \mathbb{R}^N$  be defined by  $T\mathbf{x} = \mathbf{Ax}$

Now  $T$  maps from a larger to a smaller place

This tells us that  $T$  is not one-to-one

Hence solutions are not in general unique

In fact the following is true

**Ex.** Show that  $\mathbf{Ax} = \mathbf{b}$  has a solution and  $K > N$ , then the same equation has an infinity of solutions

Remark: Working with underdetermined systems is relatively rare in economics / elsewhere