

# Interpolation, Regression, and Markov Chains

# Instructions

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# Quick RECAP

0.1. THEOREM: Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  be a linear transformation. Then there exists a unique matrix  $A$  such that

$$T(\mathbf{x}) = A(\mathbf{x}) \text{ for all } \mathbf{x} \in \mathbb{R}^n.$$

$A$  is the  $m \times n$  matrix whose  $j$ th column is the vector  $T(\mathbf{e}_j)$ , where  $\mathbf{e}_j$  is the column of the identity matrix in  $\mathbb{R}^n$  :

$$A = [T(\mathbf{e}_1) \cdots T(\mathbf{e}_n)].$$

0.2.  $A$  is called the **STANDARD MATRIX** for the linear transformation

# Quick RECAP

0.3. Let  $T : \mathbb{P}_2 \rightarrow \mathbb{P}_3$  be a linear transformation defined by

$$T(f(x)) = (x + 1)f(x).$$

Basis for  $\mathbb{P}_2$  is  $\mathcal{B} = \{1, x, x^2\}$  and Basis for  $\mathbb{P}_3$  is  $\mathcal{C} = \{1, x, x^2, x^3\}$ .

The representation matrix  $A$  for  $T$  is given by  $A = [ [T(1)]_{\mathcal{C}} \ [T(x)]_{\mathcal{C}} \ [T(x^2)]_{\mathcal{C}} ]$ .

$$T(1) = 1 + x, \quad T(x) = x + x^2, \quad T(x^2) = x^2 + x^3$$

# Quick RECAP

$$[T(1)]_c = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \quad [T(x)]_c = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \quad [T(x^2)]_c = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Hence, the representation matrix  $A$  for the transformation  $T$  is given by

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}.$$

# Interpolation, Regression and Markov Chains

Let  $A$  be an  $m \times n$  matrix,  $\mathbf{x} \in \mathbb{R}^n$  and  $\mathbf{b} \in \mathbb{R}^m$  and let  $A\mathbf{x} = \mathbf{b}$ .

1. The system of linear equations  $A\mathbf{x} = \mathbf{b}$  is:

i). Consistent - (has at least one solution) - if  $\mathbf{b} \in \text{Col } A \subset \mathbb{R}^m$ .

ii). Inconsistent - (has no solution) - if  $\mathbf{b} \notin \text{Col } A$ .

2. i). What happens if  $\mathbf{b} \notin \text{Col } A$ ?

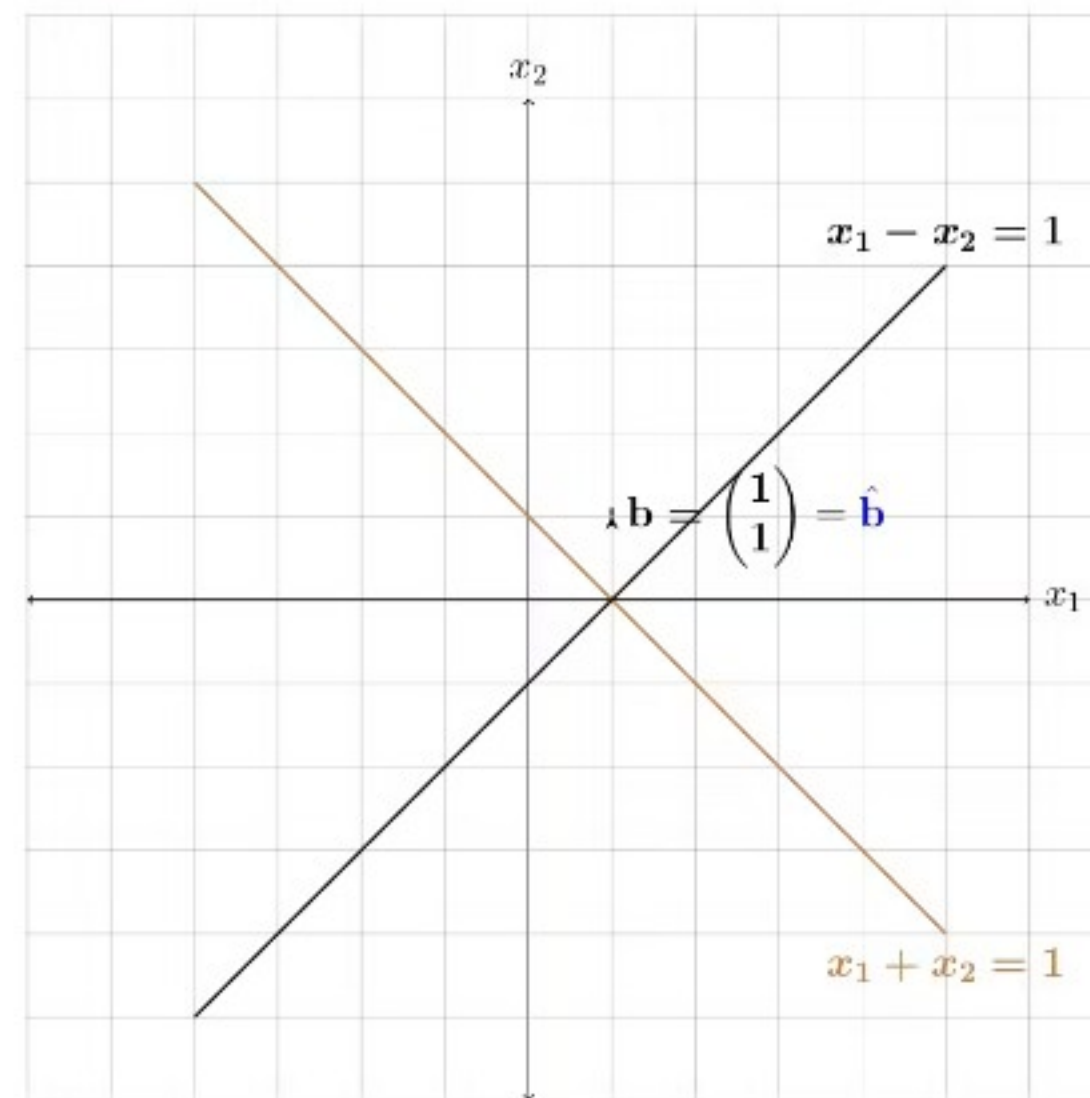
ii). We can only approximate  $\mathbf{b}$  using  $A\mathbf{x}$ .

**DIAGRAM 1 - Consistent system - Unique solution**

Consider the system of equations:

$$(0.1) \quad \begin{aligned} x_1 - x_2 &= 1 \\ x_1 + x_2 &= 1 \end{aligned} \quad \text{and} \quad \underbrace{\begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} 1 \\ 1 \end{pmatrix}}_b$$

- $A \sim \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$  and  $\text{Col}A = \text{Sp}\left\{\begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right\} = \mathbb{R}^2$ .
- $\hat{\mathbf{b}} = P_{\text{Col}A}\mathbf{b} = \mathbf{b} \in \text{Col}A$



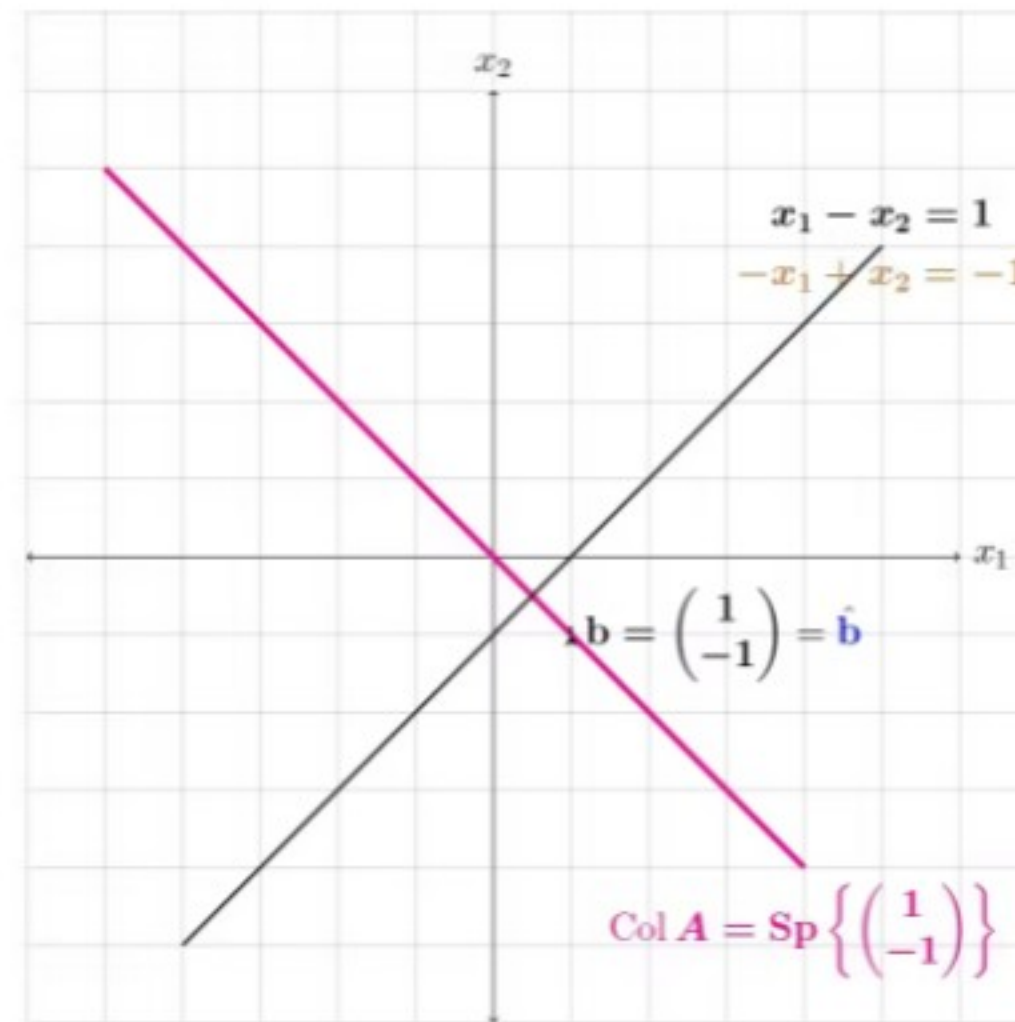
**DIAGRAM 2 - Consistent system - Infinitely many solutions**

Consider the system of equations:

$$(0.1) \quad \begin{array}{l} x_1 - x_2 = 1 \\ -x_1 + x_2 = -1 \end{array} \quad \text{and} \quad \underbrace{\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} 1 \\ -1 \end{pmatrix}}_b.$$

- $(A|\mathbf{b}) \sim \left( \begin{array}{cc|c} 1 & -1 & 1 \\ 0 & 0 & 0 \end{array} \right)$  and  $\text{Col } A = \text{Sp} \left\{ \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\} \neq \mathbb{R}^2$ .

- $\hat{\mathbf{b}} = P_{\text{Col } A} \mathbf{b} = \mathbf{b} \in \text{Col } A$



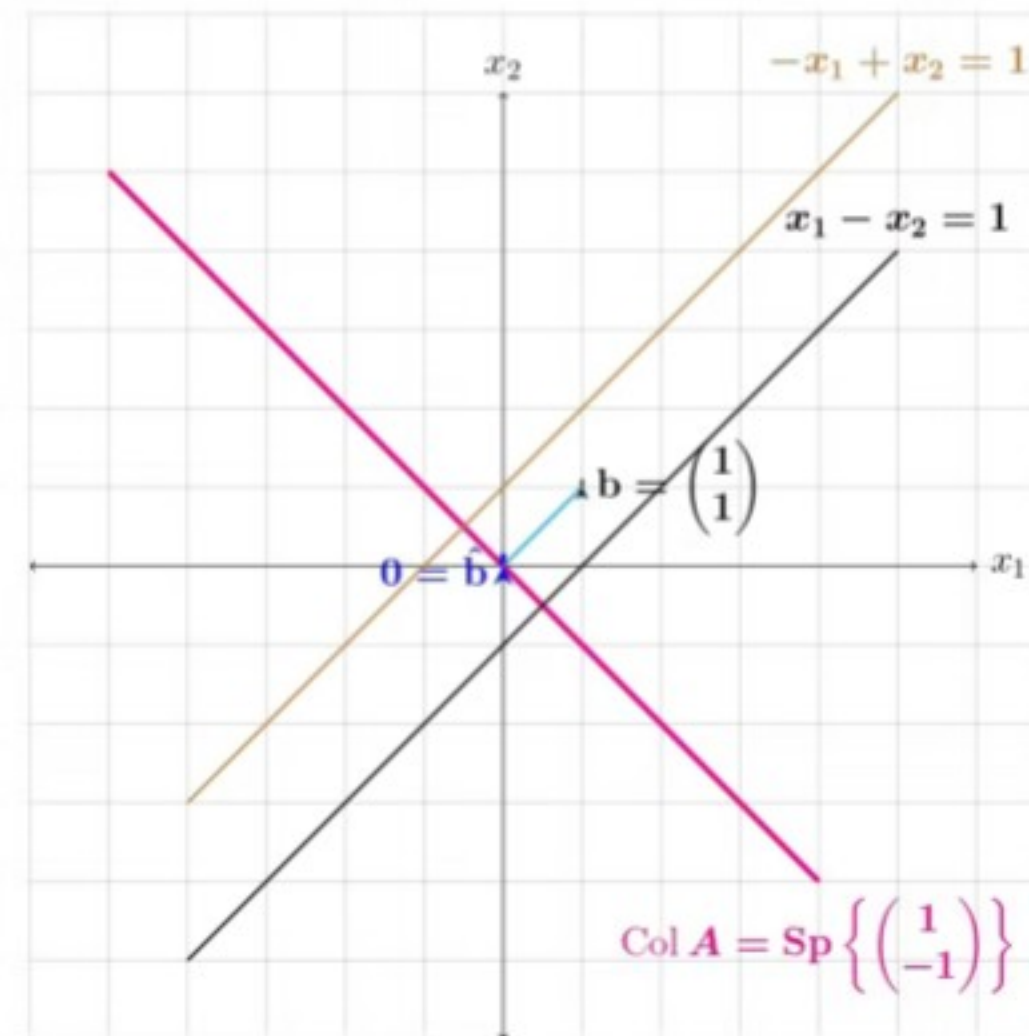


**DIAGRAM 3 - Inconsistent system - No solution**

Consider the system of equations:

$$(0.1) \quad \begin{array}{l} x_1 - x_2 = 1 \\ -x_1 + x_2 = 1 \end{array} \quad \text{and} \quad \underbrace{\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} 1 \\ 1 \end{pmatrix}}_b.$$

- $(A|b) \sim \left( \begin{array}{cc|c} 1 & -1 & 1 \\ 0 & 0 & 2 \end{array} \right)$  and  $\text{Col } A = \text{Sp} \left\{ \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\} \neq \mathbb{R}^2$ .
- $\hat{\mathbf{b}} = P_{\text{Col } A} \mathbf{b} = \mathbf{0} \in \text{Col } A$



# Interpolation, Regression and Markov Chains

3. **Definition** : If  $A$  is an  $m \times n$  matrix and  $\mathbf{b} \in \mathbb{R}^m$ , then a least-squares solution of  $A\mathbf{x} = \mathbf{b}$  is an element  $\hat{\mathbf{x}} \in \mathbb{R}^n$  such that

$$\|\mathbf{b} - A\hat{\mathbf{x}}\| \leq \|\mathbf{b} - A\mathbf{x}\|$$

for all  $\mathbf{x} \in \mathbb{R}^n$ .

4. By the **Orthogonal Decomposition** :  $A^T(A\mathbf{x} - \mathbf{b}) = 0$ .

5. **Normal Equations** :  $A^T A\mathbf{x} = A^T \mathbf{b}$ .

# Interpolation, Regression and Markov Chains

6. **Theorem** : Every solution of the normal equation  $A^T A \mathbf{x} = A^T \mathbf{b}$  is a least-squares solution of the equation  $A \mathbf{x} = \mathbf{b}$ .

7. Let  $A$  be an  $m \times n$  matrix. Then the following are equivalent:

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

ii). The matrix  $A^T A$  is invertible.

iii). The columns of  $A$  are linearly independent.

**Let  $A$  be an  $m \times n$  matrix. Then the matrix  $A^T A$  is always symmetric.**



TRUE



FALSE

# Interpolation, Regression and Markov Chains

8. **Probability vector** : A vector  $v$  with nonnegative entries that sum up to 1.

9. **Stochastic matrix** : A square matrix whose columns are probability vectors.

10. **Definition** : Let  $M$  be a stochastic matrix and  $x_0$  is a probability vector. For  $n = 0, 1, 2, \dots$ , we call the sequence of vectors  $\{x_n\}$  a **Markov chain**.

# Every unit vector is a probability vector.



TRUE



FALSE



# Every probability vector is a unit vector.



TRUE



FALSE



# The identity matrix is a stochastic matrix.



TRUE



FALSE





# Interpolation, Regression and Markov Chains

11. **Theorem** : A stochastic matrix  $M$  always has  $\lambda = 1$  as an eigenvalue.

12. **Equilibrium or steady – state vector** : Is a probability vector, which is also an eigenvector corresponding to the eigenvalue 1 of a stochastic matrix  $M$ .

13. **Regular Stochastic Matrix** : A stochastic matrix  $M$  is called regular if there is a  $k \geq 1$  such that all the elements in  $M^k$  are strictly positive (.i.e.  $> 0$ ).

# Interpolation, Regression and Markov Chains

14. **Theorem** : Let  $M$  be a regular stochastic matrix. Then  $M$  has a unique equilibrium vector  $q$ .  
For any initial probability vector  $x_0$ , the Markov chain  $\{x_n\}$  converges to  $q$   
when  $n \rightarrow \infty$ .

**A stochastic triangular matrix is  
regularly stochastic.**



TRUE



FALSE



The matrix  $M = \begin{pmatrix} 0.4 & 0.2 \\ 0.2 & 0.7 \\ 0.4 & 0.1 \end{pmatrix}$  is  
stochastic.



TRUE

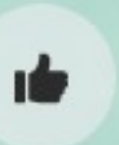


FALSE



The matrix  $M = \begin{pmatrix} 0.4 & 0.2 & 1 \\ 0.2 & 0.7 & 0 \\ 0.5 & 0.1 & 0 \end{pmatrix}$  is  
stochastic.

TRUE
  FALSE



The matrix  $M = \begin{pmatrix} 0 & 0.3 \\ 1 & 0.7 \end{pmatrix}$  is regularly  
stochastic.



TRUE




FALSE

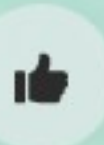
**Find the equilibrium or steady-state vector**

**of**  $M = \begin{pmatrix} 0.1 & 0.3 \\ 0.9 & 0.7 \end{pmatrix}$ .

  
 $(1/2, 1/2)$

  
 $(1/3, 2/3)$

  
 $(1/4, 3/4)$



## QUESTIONS - 40 MINUTES

1. Use the least-squares method to find
  - i. the linear polynomial and
  - ii. the quadratic polynomial
 that best fit the data points  $(1, -2)$ ,  $(0, 3)$ ,  $(0, 1)$ ,  $(1, 0)$ , and  $(-1, 1)$ .
  
2. Let the matrix  $M = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$  be a stochastic matrix.
  - i. Show that  $M$  has at least one equilibrium or steady-state vector.
  - ii. Show that  $M$  can be written in the form  $\begin{bmatrix} 1-c & b \\ c & 1-b \end{bmatrix}$ , where  $b, c \in (0, 1)$ .
  - iii. If  $b = c = 0$ , then prove that there are two linearly independent equilibrium vectors.
  
3. Decide whether or not each of the following matrices  $M$  is regularly stochastic. If yes, find the matrix  $M^k$  for some  $k \geq 1$  whose entries are strictly positive, and find the equilibrium or steady-state vector of  $M$ .

i.  $\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

ii.  $\begin{bmatrix} 0 & 1 & 0.5 \\ 0.4 & 0 & 0 \\ 0.6 & 0 & 0.5 \end{bmatrix}$