

AMES Class Notes – Week 9, Monday: Linear Algebra, cont

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1 Squaring matrices

Consider a matrix $V_{N \times 1}$ that you'd like to square.

$$V^2 = V_{1 \times N}^T V_{N \times 1} \quad (1)$$

$$= Z_{1 \times 1} \quad (2)$$

Sometimes you'll have a weighting matrix, $M_{N \times N}$

$$V_{1 \times N}^T M_{N \times N} V_{N \times 1} = Z_{1 \times 1} \quad (3)$$

2 Idempotent matrix

Defn: A matrix that when squared equals itself

$$Z^T Z = Z \quad (4)$$

This property means that applying the matrix operation twice (or any number of times) has the same effect as applying it once.

3 Kronecker product

You see this in computer algorithms and data management problems. It's a common trick. It's technically a "tensor" operation. A tensor is a 3⁺D matrix object.

The **Kronecker product** is an operation that takes two matrices and produces a larger matrix by multiplying each element of the first matrix by the entire second matrix. If A is an $m \times n$ matrix and B is a $p \times q$ matrix, then the Kronecker product $A \otimes B$ is an $mp \times nq$ block matrix, where each entry a_{ij} in A is replaced by the block $a_{ij}B$.

Definition

For matrices $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ and $B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, the Kronecker product $A \otimes B$ is:

$$A \otimes B = \begin{bmatrix} a_{11}B & a_{12}B \\ a_{21}B & a_{22}B \end{bmatrix} = \begin{bmatrix} a_{11}b_{11} & a_{11}b_{12} & a_{12}b_{11} & a_{12}b_{12} \\ a_{11}b_{21} & a_{11}b_{22} & a_{12}b_{21} & a_{12}b_{22} \\ a_{21}b_{11} & a_{21}b_{12} & a_{22}b_{11} & a_{22}b_{12} \\ a_{21}b_{21} & a_{21}b_{22} & a_{22}b_{21} & a_{22}b_{22} \end{bmatrix}$$

The Kronecker product is widely used in signal processing, control theory, and other fields where constructing block matrices is essential.

4 Trace of a Matrix

The **trace** of a matrix is the sum of the elements along its *main diagonal* (the diagonal that runs from the top left to the bottom right of the matrix).

Definition

For a square matrix A of size $n \times n$:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix},$$

the trace of A , denoted as $\text{tr}(A)$, is given by:

$$\text{tr}(A) = a_{11} + a_{22} + \cdots + a_{nn} = \sum_{i=1}^n a_{ii}.$$

5 Rank of a Matrix

The **rank** of a matrix is the dimension of the *column space* (or *row space*) of the matrix. Intuitively, it represents the maximum number of linearly independent columns (or rows) in the matrix.

For a matrix A :

- The *column space* of A consists of all possible linear combinations of its columns.
- The rank tells us the number of independent directions in the space spanned by the columns.

Properties of Rank

1. **Range:** The rank of an $m \times n$ matrix A is at most $\min(m, n)$.
2. **Full Rank:**
 - If the rank of A is equal to n (for an $m \times n$ matrix), then A is said to have *full column rank*, meaning all columns are linearly independent.
 - Note: the dimensions of a matrix are always given rows by columns, which is why we know that n is referring to the number of columns.
 - If the rank of A is equal to m , then A has *full row rank*.

The rank is fundamental in linear algebra, especially for solving linear systems, determining invertibility, and performing dimensionality reduction in applications such as data science.

6 Linear regression

Consider the equation estimating equation

$$y = a + bx + cz + \epsilon \quad (5)$$

We can rewrite this as

$$\underset{N \times 1}{Y} = \underset{N \times K}{X} \underset{K \times 1}{\beta} + \underset{N \times 1}{\epsilon} \quad (6)$$

$$(7)$$

where

$$\beta = \begin{bmatrix} a \\ b \\ c \end{bmatrix} \quad (8)$$

$$X = \begin{bmatrix} 1 & x_1 & z_1 \\ 1 & x_2 & z_2 \\ \vdots & \dots & \end{bmatrix} \quad (9)$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \end{bmatrix} \quad (10)$$

Goal: Solve for β by minimizing the sum of square errors.

Solve for the error term:

$$\underset{N \times 1}{Y} - \underset{N \times K}{X} \underset{K \times 1}{\beta} = \underset{N \times 1}{\epsilon} \quad (11)$$

Square the error term:

$$\underset{1 \times N}{\epsilon}^T \underset{N \times 1}{\epsilon} = (\underset{1 \times N}{Y} - \underset{N \times 1}{X} \underset{K \times 1}{\beta})^T (\underset{1 \times N}{Y} - \underset{N \times 1}{X} \underset{K \times 1}{\beta}) \quad (12)$$

$$= \underset{1 \times N}{Y}^T \underset{N \times 1}{Y} - \underset{1 \times K}{\beta}^T \underset{K \times N}{X}^T \underset{N \times 1}{Y} - \underset{1 \times N}{Y}^T \underset{N \times K}{X} \underset{K \times 1}{\beta} + \underset{1 \times K}{\beta}^T \underset{K \times N}{X}^T \underset{N \times K}{X} \underset{K \times 1}{\beta} \quad (13)$$

$$= \underset{1 \times 1}{Y}^T \underset{1 \times 1}{Y} - 2 \underset{1 \times 1}{\beta}^T \underset{1 \times 1}{X}^T \underset{1 \times 1}{Y} + \underset{1 \times 1}{\beta}^T \underset{1 \times 1}{X}^T \underset{1 \times 1}{X} \underset{1 \times 1}{\beta} \quad (14)$$

The squared error term is a scalar $\underset{(1 \times 1)}{\epsilon}^T \epsilon$.

We want to find the β that minimizes the sum of squared errors. To do so, take derivative of squared error wrt to β^T and set equal to zero, then solve for β .

$$\frac{\partial \epsilon^T \epsilon}{\partial \beta} = 0 - 2 \underset{K \times 1}{X}^T \underset{N \times 1}{Y} + 2 \underset{K \times 1}{X}^T \underset{N \times K}{X} \underset{K \times 1}{\beta} = 0 \implies \quad (15)$$

$$2 \underset{K \times 1}{X}^T \underset{N \times 1}{Y} = 2 \underset{K \times 1}{X}^T \underset{N \times K}{X} \underset{K \times 1}{\beta} \implies \quad (16)$$

$$\beta = (\underset{K \times K}{X}^T \underset{N \times K}{X})^{-1} \underset{K \times 1}{X}^T \underset{N \times 1}{Y} \quad (17)$$

Where $(\underset{K \times K}{X}^T \underset{N \times K}{X})^{-1}$ is an inversion (because we cannot divide matrices).

We have solved for β , which is a vector of all the parameters that we saw in equation ?? (look at equation ??). Remember, the first element of β is the intercept *because* the first column of \mathbf{X} is all 1s (rather than any variable). The column of 1s is important and forces the first element of β to be the intercept.

7 Life cycle assessment example

Let's consider an input output table (Ag, Transportation, Manufactured)

$$A = \begin{bmatrix} & A & T & M \\ A & & & \\ T & & & \\ M & & & \end{bmatrix}_{3 \times 3} \quad (18)$$

And our final demand (the demand for goods by consumers)

$$d = \begin{bmatrix} A \\ T \\ M \end{bmatrix}_{3 \times 1} \quad (19)$$

Total amount of goods X is,

$$X_{3 \times 1} = A_{3 \times 3} X_{3 \times 1} + d_{3 \times 1} \quad (20)$$

Solve for X by multiplying with the identity matrix

$$I_{3 \times 3} X - AX = d \quad (21)$$

$$(I - A)X = d \quad (22)$$

$$\implies (I - A)^{-1}d = X \quad (23)$$

Total amount of goods is different than final demand because we need input good for the final good. A bunch of intermediate products are required to make a computer.

8 R and Excel

Watch the video! Couple of notes

- to invert a matrix in R you use the `solve()` command