# Matrix Refresher 

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${ }^{1}$ These slides borrow liberally from Matt Blackwell and Adam Glynn.

## Where We've Been and Where We're Going...

- Lecture 7 presents the full matrix version of OLS. These slides provide a compact summary of the key matrix concepts that are necessary to follow along.
- Khan Academy provides a number of other great linear algebra resources.
- You might also find the following books helpful:
- Essential Mathematics for Political and Social Research by Jeff Gill
- A Mathematics Course for Political \& Social Research by Moore and Siegel
- Both books are designed to cover the mathematical content for this particular kind of course sequence.
- For those going on to future training, matrix representations of linear regression are the most common form you will see so it is good to have the basics.


## Why Matrices and Vectors?

Here's one way to write the full multiple regression model:

$$
y_{i}=\beta_{0}+x_{i 1} \beta_{1}+x_{i 2} \beta_{2}+\cdots+x_{i K} \beta_{K}+u_{i}
$$

- Notation is going to get needlessly messy as we add variables
- Matrices are clean, but they are like a foreign language
- They make take some practice but it will make everything substantially more general


## Matrices and Vectors

- A matrix is just a rectangular array of numbers.
- We say that a matrix is $n \times p$ (" $n$ by $p$ ") if it has $n$ rows and $p$ columns.
- Uppercase bold denotes a matrix:

$$
\mathbf{A}=\left[\begin{array}{cccc}
a_{11} & a_{12} & \cdots & a_{1 p} \\
a_{21} & a_{22} & \cdots & a_{2 p} \\
\vdots & \vdots & \ddots & \vdots \\
a_{n 1} & a_{n 2} & \cdots & a_{n p}
\end{array}\right]
$$

- Generic entry: $a_{i j}$ where this is the entry in row $i$ and column $j$


## Design Matrix

One example of a matrix that we'll use a lot is the design matrix, which has a column of ones, and then each of the subsequent columns is each independent variable in the regression.

$$
\mathbf{X}=\left[\begin{array}{cccc}
1 & \text { exports }_{1} & \text { age }_{1} & \text { male }_{1} \\
1 & \text { exports }_{2} & \text { age }_{2} & \text { male }_{2} \\
\vdots & \vdots & \vdots & \vdots \\
1 & \text { exports }_{n} & \text { age }_{n} & \text { male }_{n}
\end{array}\right]
$$

## Vectors

- A vector is just a matrix with only one row or one column.
- A row vector is a vector with only one row, sometimes called a $1 \times p$ vector:

$$
\boldsymbol{\alpha}=\left[\begin{array}{lllll}
\alpha_{1} & \alpha_{2} & \alpha_{3} & \cdots & \alpha_{p}
\end{array}\right]
$$

- A column vector is a vector with one column and more than one row. Here is a $n \times 1$ vector:

$$
\mathbf{y}=\left[\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
y_{n}
\end{array}\right]
$$

- Convention: we'll assume that a vector is column vector and (when we are being formal) vectors will be written with lowercase bold lettering (b).
NB: I'm not completely consistent about bolding vectors and matrices. If you are unclear about the dimensionality of an object (is it a scalar? a vector? a matrix?) just ask.


## Vector Examples

One common vector that we will work with are individual variables, such as the dependent variable, which we will represent as $\mathbf{y}$ :

$$
\mathbf{y}=\left[\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
y_{n}
\end{array}\right]
$$

## Transpose

- There are many operations we'll do on vectors and matrices, but one is very fundamental: the transpose.
- The transpose of a matrix $\mathbf{A}$ is the matrix created by switching the rows and columns of the data and is denoted $\mathbf{A}^{\prime}$. That is, the $p$ th column becomes the $p$ th row.

$$
\mathbf{Q}=\left[\begin{array}{ll}
q_{11} & q_{12} \\
q_{21} & q_{22} \\
q_{31} & q_{32}
\end{array}\right] \quad \mathbf{Q}^{\prime}=\left[\begin{array}{lll}
q_{11} & q_{21} & q_{31} \\
q_{12} & q_{22} & q_{32}
\end{array}\right]
$$

If $\mathbf{A}$ is of dimension $n \times p$, then $\mathbf{A}^{\prime}$ will be dimension $p \times n$.

## Transposing Vectors

Transposing will turn a $p \times 1$ column vector into a $1 \times p$ row vector and vice versa:

$$
\boldsymbol{\omega}=\left[\begin{array}{r}
1 \\
3 \\
2 \\
-5
\end{array}\right] \quad \boldsymbol{\omega}^{\prime}=\left[\begin{array}{llll}
1 & 3 & 2 & -5
\end{array}\right]
$$

## Write matrices as vectors

- A matrix is just a collection of vectors (row or column)
- As a row vector:

$$
\mathbf{A}=\left[\begin{array}{lll}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23}
\end{array}\right]=\left[\begin{array}{l}
\mathbf{a}_{1}^{\prime} \\
\mathbf{a}_{2}^{\prime}
\end{array}\right]
$$

with row vectors $\mathbf{a}_{1}^{\prime}=\left[\begin{array}{lll}a_{11} & a_{12} & a_{13}\end{array}\right] \mathbf{a}_{2}^{\prime}=\left[\begin{array}{lll}a_{21} & a_{22} & a_{23}\end{array}\right]$

- Or we can define it in terms of column vectors:

$$
\mathbf{B}=\left[\begin{array}{ll}
b_{11} & b_{12} \\
b_{21} & b_{22} \\
b_{31} & b_{32}
\end{array}\right]=\left[\begin{array}{ll}
\mathbf{b}_{\mathbf{1}} & \mathbf{b}_{\mathbf{2}}
\end{array}\right]
$$

where $\mathbf{b}_{\mathbf{1}}$ and $\mathbf{b}_{\mathbf{2}}$ represent the columns of $\mathbf{B}$.

## Addition and Subtraction

- To perform certain operations (e.g. addition, subtraction, multiplication, inversion and exponentiation) the matrices/vectors need to be conformable. Conformable means that the dimensions are suitable for defining that operation.
- Two matrices are conformable for addition or subtraction if they have the same dimensions.
- Let $\mathbf{A}$ and $\mathbf{B}$ both be $2 \times 2$ matrices. Then, let $\mathbf{C}=\mathbf{A}+\mathbf{B}$, where we add each cell together:

$$
\begin{aligned}
\mathbf{A}+\mathbf{B} & =\left[\begin{array}{ll}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{array}\right]+\left[\begin{array}{ll}
b_{11} & b_{12} \\
b_{21} & b_{22}
\end{array}\right] \\
& =\left[\begin{array}{ll}
a_{11}+b_{11} & a_{12}+b_{12} \\
a_{21}+b_{21} & a_{22}+b_{22}
\end{array}\right] \\
& =\left[\begin{array}{ll}
c_{11} & c_{12} \\
c_{21} & c_{22}
\end{array}\right] \\
& =\mathbf{C}
\end{aligned}
$$

## Scalar Multiplication

- A scalar is just a single number: you can think of it sort of like a 1 by 1 matrix.
- When we multiply a scalar by a matrix, we just multiply each element/cell by that scalar.
- Whenever we do things cell-by-cell like this we sometimes call it an elementwise/entrywise operation

$$
\alpha \mathbf{A}=\alpha\left[\begin{array}{ll}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{array}\right]=\left[\begin{array}{ll}
\alpha \times a_{11} & \alpha \times a_{12} \\
\alpha \times a_{21} & \alpha \times a_{22}
\end{array}\right]
$$

## The Linear Model with New Notation

- Remember that we wrote the linear model as the following for all $i \in[1, \ldots, n]$ :

$$
y_{i}=\beta_{0}+x_{i} \beta_{1}+z_{i} \beta_{2}+u_{i}
$$

- Imagine we had an $n$ of 4 . We could write out each formula:

$$
\begin{array}{ll}
y_{1}=\beta_{0}+x_{1} \beta_{1}+z_{1} \beta_{2}+u_{1} & (\text { unit 1) } \\
y_{2}=\beta_{0}+x_{2} \beta_{1}+z_{2} \beta_{2}+u_{2} & (\text { unit 2) } \\
y_{3}=\beta_{0}+x_{3} \beta_{1}+z_{3} \beta_{2}+u_{3} & (\text { unit 3) } \\
y_{4}=\beta_{0}+x_{4} \beta_{1}+z_{4} \beta_{2}+u_{4} & (\text { unit 4) }
\end{array}
$$

## The Linear Model with New Notation

$$
\begin{array}{ll}
y_{1}=\beta_{0}+x_{1} \beta_{1}+z_{1} \beta_{2}+u_{1} & (\text { unit 1) } \\
y_{2}=\beta_{0}+x_{2} \beta_{1}+z_{2} \beta_{2}+u_{2} & (\text { unit 2) } \\
y_{3}=\beta_{0}+x_{3} \beta_{1}+z_{3} \beta_{2}+u_{3} & (\text { unit 3) } \\
y_{4}=\beta_{0}+x_{4} \beta_{1}+z_{4} \beta_{2}+u_{4} & (\text { unit 4) }
\end{array}
$$

- We can write this as:

$$
\left[\begin{array}{l}
y_{1} \\
y_{2} \\
y_{3} \\
y_{4}
\end{array}\right]=\left[\begin{array}{l}
1 \\
1 \\
1 \\
1
\end{array}\right] \beta_{0}+\left[\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3} \\
x_{4}
\end{array}\right] \beta_{1}+\left[\begin{array}{l}
z_{1} \\
z_{2} \\
z_{3} \\
z_{4}
\end{array}\right] \beta_{2}+\left[\begin{array}{l}
u_{1} \\
u_{2} \\
u_{3} \\
u_{4}
\end{array}\right]
$$

- Outcome is a linear combination of the the $\mathbf{x}, \mathbf{z}$, and $\mathbf{u}$ vectors


## Grouping Things into Matrices

- Can we write this in a more compact form? Yes! Let $\mathbf{X}$ and $\boldsymbol{\beta}$ be the following:

$$
\underset{(4 \times 3)}{\mathbf{X}}=\left[\begin{array}{lll}
1 & x_{1} & z_{1} \\
1 & x_{2} & z_{2} \\
1 & x_{3} & z_{3} \\
1 & x_{4} & z_{4}
\end{array}\right] \quad \underset{(3 \times 1)}{\boldsymbol{\beta}}=\left[\begin{array}{l}
\beta_{0} \\
\beta_{1} \\
\beta_{2}
\end{array}\right]
$$

## Matrix multiplication by a vector

- We can write this more compactly as a matrix (post-)multiplied by a vector:

$$
\left[\begin{array}{l}
1 \\
1 \\
1 \\
1
\end{array}\right] \beta_{0}+\left[\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3} \\
x_{4}
\end{array}\right] \beta_{1}+\left[\begin{array}{l}
z_{1} \\
z_{2} \\
z_{3} \\
z_{4}
\end{array}\right] \beta_{2}=\mathbf{X} \boldsymbol{\beta}
$$

- Multiplication of a matrix by a vector is just the linear combination of the columns of the matrix with the vector elements as weights/coefficients.
- And the left-hand side here only uses scalars times vectors, which is easy!


## General Matrix by Vector Multiplication

- $\mathbf{A}$ is a $n \times p$ matrix
- $\mathbf{b}$ is a $p \times 1$ column vector
- Columns of $\mathbf{A}$ have to match rows of $\mathbf{b}$ to be conformable for matrix-vector multiplication
- Let $\mathbf{a}_{j}$ be the $j$ th column of $A$. Then we can write:

$$
\underset{(j \times 1)}{\mathbf{c}}=\mathbf{A} \mathbf{b}=b_{1} \mathbf{a}_{1}+b_{2} \mathbf{a}_{2}+\cdots+b_{p} \mathbf{a}_{p}
$$

- c is linear combination of the columns of $\mathbf{A}$


## Back to Regression

- Imagine that we have $K$ covariates, such that we have $K+1$ different $\beta$ (due to the intercept being $\beta_{0}$ ).
- $\mathbf{X}$ is the $n \times(p+1)$ design matrix of independent variables
- $\boldsymbol{\beta}$ be the $(K+1) \times 1$ column vector of coefficients.
- $\mathbf{X} \boldsymbol{\beta}$ will be $n \times 1$ :

$$
\mathbf{X} \boldsymbol{\beta}=\beta_{0}+\beta_{1} \mathbf{x}_{1}+\beta_{2} \mathbf{x}_{2}+\cdots+\beta_{K} \mathbf{x}_{K}
$$

- We can compactly write the linear model as the following:

$$
\underset{(n \times 1)}{\mathbf{y}}=\underset{(n \times 1)}{\mathbf{X} \boldsymbol{\beta}}+\underset{(n \times 1)}{\mathbf{u}}
$$

- We can also write this at the individual level, where $\mathbf{x}_{i}^{\prime}$ is the $i$ th row of $\mathbf{X}$ :

$$
y_{i}=\mathbf{x}_{i}^{\prime} \boldsymbol{\beta}+u_{i}
$$

## Matrix Multiplication

- What if, instead of a column vector $b$, we have a matrix $\mathbf{B}$ with dimensions $p \times m$.
- How do we do multiplication like so $\mathbf{C}=\mathbf{A B}$ ?
- Each column of the new matrix is just matrix by vector multiplication:

$$
\mathbf{C}=\left[\begin{array}{llll}
\mathbf{c}_{1} & \mathbf{c}_{2} & \cdots & \mathbf{c}_{m}
\end{array}\right] \quad \mathbf{c}_{i}=\mathbf{A} \mathbf{b}_{i}
$$

- Thus, each column of $\mathbf{C}$ is a linear combination of the columns of $\mathbf{A}$.


## A visual approach to matrix multiplication


https://en.wikipedia.org/wiki/Matrix_multiplication\#/media/ File:Matrix_multiplication_diagram_2.svg

## A second visual approach

Credit: https://betterexplained.com/articles/linear-algebra-guide/


Output Data


Operations to perform


Input Data

## A second visual approach

Credit: https://betterexplained.com/articles/linear-algebra-guide/


## A dynamic approach to matrix multiplication

https://www.khanacademy.org/math/precalculus/<br>precalc-matrices/multiplying-matrices-by-matrices/v/ matrix-multiplication-intro

## Properties of Matrix Multiplication

- Matrix multiplication is not commutative $\mathbf{A B} \neq \mathbf{B A}$
- It is associative and distributive

$$
\begin{aligned}
\mathbf{A}(\mathbf{B C}) & =(\mathbf{A B}) \mathbf{C} \\
\mathbf{A}(\mathbf{B}+\mathbf{C}) & =\mathbf{A B}+\mathbf{A C} \\
(\mathbf{A B})^{\prime} & =\mathbf{B}^{\prime} \mathbf{A}^{\prime}
\end{aligned}
$$

## Special Multiplications

- The inner product of a two column vectors $\mathbf{a}$ and $\mathbf{b}$ (of equal dimension, $p \times 1$ ):

$$
\mathbf{a}^{\prime} \mathbf{b}=a_{1} b_{1}+a_{2} b_{2}+\cdots+a_{p} b_{p}
$$

- Special case of above: $\mathbf{a}^{\prime}$ is a matrix with $p$ columns and just 1 row, so the "columns" of $\mathbf{a}^{\prime}$ are just scalars.


## Sum of the Squared Residuals

- Example: let's say that we have a vector of residuals, $\widehat{\mathbf{u}}$, then the inner product of the residuals is:

$$
\begin{gathered}
\hat{\mathbf{u}}^{\prime} \hat{\mathbf{u}}=\left[\begin{array}{llll}
\widehat{u}_{1} & \widehat{u}_{2} & \cdots & \widehat{u}_{n}
\end{array}\right]\left[\begin{array}{c}
\widehat{u}_{1} \\
\widehat{u}_{2} \\
\vdots \\
\widehat{u}_{n}
\end{array}\right] \\
\hat{\mathbf{u}}^{\prime} \hat{\mathbf{u}}=\widehat{u}_{1} \widehat{u}_{1}+\widehat{u}_{2} \widehat{u}_{2}+\cdots+\widehat{u}_{n} \widehat{u}_{n}=\sum_{i=1}^{n} \widehat{u}_{i}^{2}
\end{gathered}
$$

- It's just the sum of the squared residuals!


## Square Matrices and the Diagonal

- A square matrix has equal numbers of rows and columns.
- The diagonal of a square matrix are the values $a_{j j}$ :

$$
\mathbf{A}=\left[\begin{array}{lll}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{array}\right]
$$

- The identity matrix, $\mathbf{I}$ is a square matrix, with 1 s along the diagonal and $0 s$ everywhere else.

$$
\mathbf{I}=\left[\begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right]
$$

- The identity matrix multiplied by any matrix returns the matrix: $\mathbf{A l}=\mathbf{A}$.


## Scalar Inverses

- What is division in its simplest form? $\frac{1}{a}$ is the value such that $a \frac{1}{a}=1$ :
- For some algebraic expression: $a u=b$, let's solve for $u$ :

$$
\begin{aligned}
\frac{1}{a} a u & =\frac{1}{a} b \\
u & =\frac{b}{a}
\end{aligned}
$$

- Need a matrix version of this: $\frac{1}{a}$.


## Matrix Inverses

## Definition (Matrix Inverse)

If it exists, the inverse of square matrix $\mathbf{A}$, denoted $\mathbf{A}^{-1}$, is the matrix such that $\mathbf{A}^{-1} \mathbf{A}=\mathbf{I}$.

- We can use the inverse to solve (systems of) equations:

$$
\begin{aligned}
\mathbf{A u} & =\mathbf{b} \\
\mathbf{A}^{-1} \mathbf{A} \mathbf{u} & =\mathbf{A}^{-1} \mathbf{b} \\
\mathbf{l} \mathbf{u} & =\mathbf{A}^{-1} \mathbf{b} \\
\mathbf{u} & =\mathbf{A}^{-1} \mathbf{b}
\end{aligned}
$$

- If the inverse exists, we say that $\mathbf{A}$ is invertible or nonsingular.

