

# Chapter 6

## Linear Independence

# Linear Dependence/Independence

A set of vectors  $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p\}$  is **linearly dependent** if we can express the zero vector,  $\mathbf{0}$ , as a *non-trivial* linear combination of the vectors.

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_p \mathbf{v}_p = \mathbf{0}$$

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The set  $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p\}$  is **linearly independent** if the above equation has only the trivial solution,  $\alpha_1 = \alpha_2 = \dots = \alpha_p = 0$ .

# Linear Dependence - Example

The vectors  $\mathbf{v}_1 = \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix}$ ,  $\mathbf{v}_2 = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}$ , and  $\mathbf{v}_3 = \begin{pmatrix} 3 \\ 6 \\ 7 \end{pmatrix}$  are **linearly dependent** because

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**# Perfect Multicollinearity!**

# Example - Determining Linear Independence

$\mathbf{v}_1 = \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix}$ ,  $\mathbf{v}_2 = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}$ , and  $\mathbf{v}_3 = \begin{pmatrix} 3 \\ 6 \\ 7 \end{pmatrix}$  How can we tell if these vectors are linearly independent?

- Want to know if there are coefficients  $\alpha_1, \alpha_2, \alpha_3$  such that

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \alpha_3 \mathbf{v}_3 = \mathbf{0}$$

- This creates a linear system!

$$\begin{pmatrix} 1 & 1 & 3 \\ 2 & 2 & 6 \\ 2 & 3 & 7 \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

- Just use Gauss-Jordan elimination to find out that

$$\begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} = \begin{pmatrix} 2 \\ 1 \\ -1 \end{pmatrix}$$

is one possible solution (there are free variables)!

# Example - Determining Linear Independence

For a set of vectors  $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$ ,

- If the only solution was the trivial solution,

$$\begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

Then we'd know that  $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$  are linearly independent.

- $\implies$  no free variables! Gauss-Jordan elimination on the vectors results in the identity matrix:

$$\left( \begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{array} \right)$$



# Summary - Determining Linear Independence

The sum from our definition,

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \cdots + \alpha_p \mathbf{v}_p = \mathbf{0},$$

is simply a matrix-vector product

$$\mathbf{V}\boldsymbol{\alpha} = \mathbf{0}$$

where  $\mathbf{V} = (\mathbf{v}_1 \mid \mathbf{v}_2 \mid \cdots \mid \mathbf{v}_p)$  and  $\boldsymbol{\alpha} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_p \end{pmatrix}$

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So all we need to do is determine whether the system of equations  $\mathbf{V}\boldsymbol{\alpha} = \mathbf{0}$  has any non-trivial solutions.

# Rank and Linear Independence

- If a set of vectors (think: *variables*) is not linearly independent, then the matrix that contains those vectors as columns (think: *data matrix*) is not full rank!
- The **rank** of a matrix can be defined as the number of linearly independent columns (or rows) in that matrix.
  - # of linearly independent rows = # of linearly independent columns
- In most data - # of rows  $>$  # of columns.
- So the maximum rank of a matrix is the # of columns - an  $n \times m$  full rank matrix has  $rank = m$ .

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- $\mathbf{A}$  is invertible ( $\mathbf{A}^{-1}$  exists)
- $\mathbf{A}$  has full rank ( $\text{rank}(\mathbf{A}) = n$ )
- The columns of  $\mathbf{A}$  are linearly independent
- The rows of  $\mathbf{A}$  are linearly independent
- The system  $\mathbf{Ax} = \mathbf{b}$  has a unique solution
- $\mathbf{Ax} = \mathbf{0} \implies \mathbf{x} = \mathbf{0}$
- $\mathbf{A}$  is nonsingular
- $\mathbf{A} \xrightarrow{\text{Gauss-Jordan}} \mathbf{I}$

# Check your understanding

Let  $\mathbf{a} = \begin{pmatrix} 1 \\ 3 \\ 4 \end{pmatrix}$  and  $\mathbf{b} = \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix}$ .

- Are the vectors  $\mathbf{a}$  and  $\mathbf{b}$  linearly independent?

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- What is the rank of the matrix  $\mathbf{A} = (\mathbf{a}|\mathbf{b})$ ?
- Determine whether or not the vector  $\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$  is a linear combination of the vectors  $\mathbf{a}$  and  $\mathbf{b}$ .



## Check your understanding - Solution

Let  $\mathbf{a} = \begin{pmatrix} 1 \\ 3 \\ 4 \end{pmatrix}$  and  $\mathbf{b} = \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix}$ .

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Yes. The equation  $\alpha_1 \mathbf{a} + \alpha_2 \mathbf{b} = \mathbf{0}$  has only the trivial solution

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Yes. The equation  $\alpha_1 \mathbf{a} + \alpha_2 \mathbf{b} = \mathbf{0}$  has only the trivial solution
- What is the rank of the matrix  $\mathbf{A} = (\mathbf{a}|\mathbf{b})$ ? Is  $\mathbf{A}$  full rank?  
 $\text{rank}(\mathbf{A}) = 2$  because there are two linearly independent columns.  $\mathbf{A}$  is full rank.

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*rank(A) = 2 because there are two linearly independent columns. A is full rank.*

- Determine whether or not the vector  $\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$  is a linear combination of the vectors  $\mathbf{a}$  and  $\mathbf{b}$ .

Row reduce the augmented matrix:

$$\left( \begin{array}{cc|c} 1 & 3 & 1 \\ 3 & 0 & 0 \\ 4 & 1 & 1 \end{array} \right)$$

to find that the system is inconsistent.  $\implies$  No.

# Why the fuss?

If our design matrix  $\mathbf{X}$  is not full rank, then the matrix from the normal equations,  $\mathbf{X}^T\mathbf{X}$  is also not full rank.

- $\mathbf{X}^T\mathbf{X}$  does not have an inverse.
- The normal equations do not have a unique solution!
- $\beta$ 's not uniquely determined.
- Infinitely many solutions.
- #PerfectMulticollinearity
- Breaks a fundamental assumption of MLR.

## Example - Perfect vs. Severe Multicollinearity

Often times we'll run into a situation where variables are linearly independent, but only barely so. Take, for example, the following system of equations:

$$\beta_1 \mathbf{x}_1 + \beta_2 \mathbf{x}_2 = \mathbf{y}$$

where

$$\mathbf{x}_1 = \begin{pmatrix} 0.835 \\ 0.333 \end{pmatrix} \quad \mathbf{x}_2 = \begin{pmatrix} 0.667 \\ 0.266 \end{pmatrix} \quad \mathbf{y} = \begin{pmatrix} 0.168 \\ 0.067 \end{pmatrix}$$

This system has an exact solution,  $\beta_1 = 1$  and  $\beta_2 = -1$ .

## Example - Perfect vs. Severe Multicollinearity

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If we change this system only slightly, so that  $\mathbf{y} = \begin{pmatrix} 0.168 \\ 0.066 \end{pmatrix}$  then the exact solution changes drastically to

$$\beta_1 = -666 \text{ and } \beta_2 = 834$$

.

The system is **unstable** because the columns of the matrix are so close to being linearly dependent!

# Symptoms of Severe Multicollinearity

- Large fluctuations or flips in sign of the coefficients when a collinear variable is added into the model.
- Changes in significance when additional variables are added.
- Overall F-test shows significance when the individual t-tests show none.

These symptoms are bad enough on their own, but the real consequence of this type of behavior is that seen in the previous example. A very small change in the underlying system of equations (like a minuscule change in a target value  $y_i$ ) can produce dramatic changes to our parameter estimates!