## Flash Cards

to accompany

# A First Course in Linear Algebra

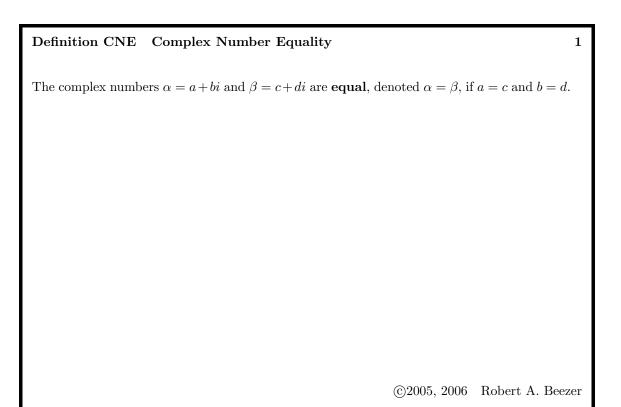
by Robert A. Beezer Department of Mathematics and Computer Science University of Puget Sound

Version 1.08

## © 2004 Robert A. Beezer.

Permission is granted to copy, distribute and/or modify this document under the terms of the GNU Free Documentation License, Version 1.2 or any later version published by the Free Software Foundation; with no Invariant Sections, no Front-Cover Texts, and no Back-Cover Texts. A copy of the GNU Free Documentation License can be found at http://www.gnu.org/copyleft/fdl.html and is incorporated here by this reference.

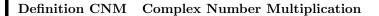
The most recent version of this work can always be found at http://linear.ups.edu.



## Definition CNA Complex Number Addition

 $\mathbf{2}$ 

The **sum** of the complex numbers  $\alpha = a + bi$  and  $\beta = c + di$ , denoted  $\alpha + \beta$ , is (a+c) + (b+d)i.



The **product** of the complex numbers  $\alpha = a + bi$  and  $\beta = c + di$ , denoted  $\alpha\beta$ , is (ac - bd) + (ad + bc)i.

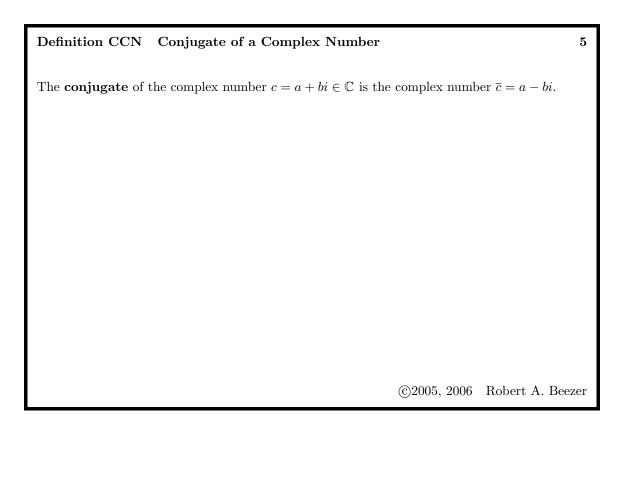
© 2005, 2006 Robert A. Beezer

3

#### Theorem PCNA Properties of Complex Number Arithmetic

The operations of addition and multiplication of complex numbers have the following properties.

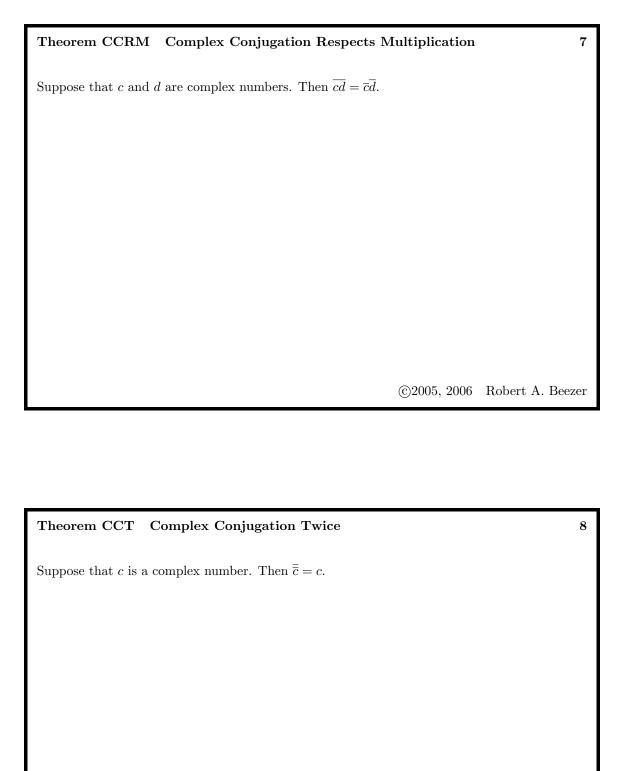
- ACCN Additive Commutativity, Complex Numbers For any  $\alpha$ ,  $\beta \in \mathbb{C}$ ,  $\alpha + \beta = \beta + \alpha$ .
- MCCN Multiplicative Commutativity, Complex Numbers For any  $\alpha, \beta \in \mathbb{C}$ ,  $\alpha\beta = \beta\alpha$ .
- AACN Additive Associativity, Complex Numbers For any  $\alpha, \beta, \gamma \in \mathbb{C}$ ,  $\alpha + (\beta + \gamma) = (\alpha + \beta) + \gamma$ .
- MACN Multiplicative Associativity, Complex Numbers For any  $\alpha, \beta, \gamma \in \mathbb{C}$ ,  $\alpha(\beta\gamma) = (\alpha\beta)\gamma$ .
- DCN Distributivity, Complex Numbers For any  $\alpha, \beta, \gamma \in \mathbb{C}$ ,  $\alpha(\beta + \gamma) = \alpha\beta + \alpha\gamma$ .
- **ZCN Zero, Complex Numbers** There is a complex number 0 = 0 + 0i so that for any  $\alpha \in \mathbb{C}$ ,  $0 + \alpha = \alpha$ .
- OCN One, Complex Numbers There is a complex number 1 = 1 + 0i so that for any  $\alpha \in \mathbb{C}$ ,  $1\alpha = \alpha$ .
- AICN Additive Inverse, Complex Numbers For every  $\alpha \in \mathbb{C}$  there exists  $-\alpha \in \mathbb{C}$  so that  $\alpha + (-\alpha) = 0$ .
- MICN Multiplicative Inverse, Complex Numbers For every  $\alpha \in \mathbb{C}$ ,  $\alpha \neq 0$  there exists  $\frac{1}{\alpha} \in \mathbb{C}$  so that  $\alpha\left(\frac{1}{\alpha}\right) = 1$ .

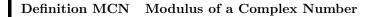


## Theorem CCRA Complex Conjugation Respects Addition

6

Suppose that c and d are complex numbers. Then  $\overline{c+d} = \overline{c} + \overline{d}$ .





a

The **modulus** of the complex number  $c = a + bi \in \mathbb{C}$ , is the nonnegative real number

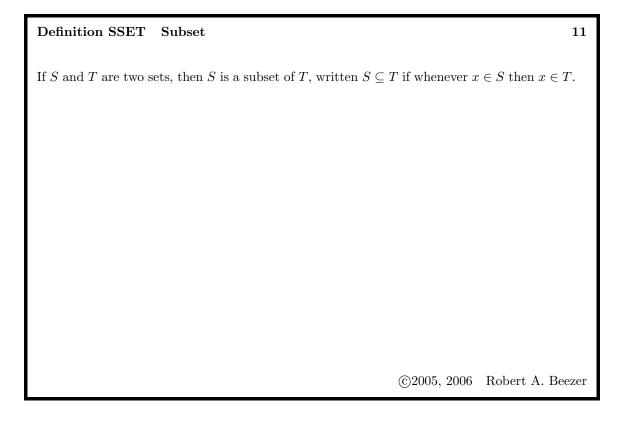
$$|c| = \sqrt{c\overline{c}} = \sqrt{a^2 + b^2}.$$

©2005, 2006 Robert A. Beezer

## Definition SET Set

**10** 

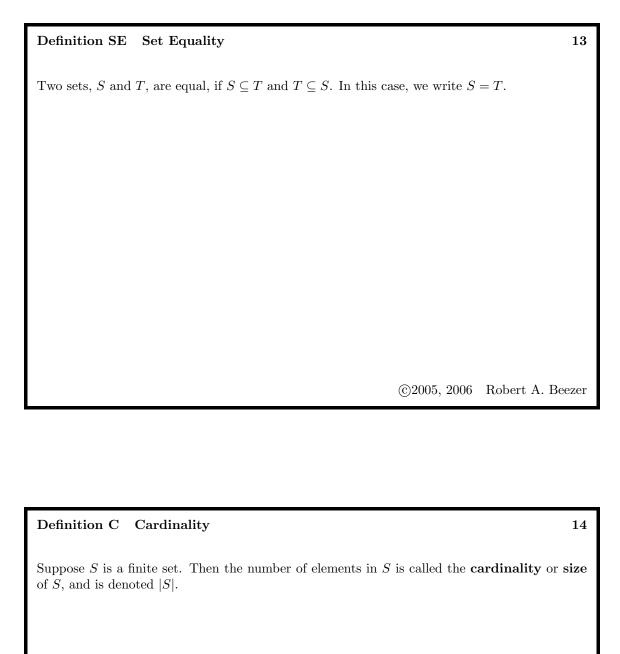
A set is an unordered collection of objects. If S is a set and x is an object that is in the set S, we write  $x \in S$ . If x is not in S, then we write  $x \notin S$ . We refer to the objects in a set as its elements.

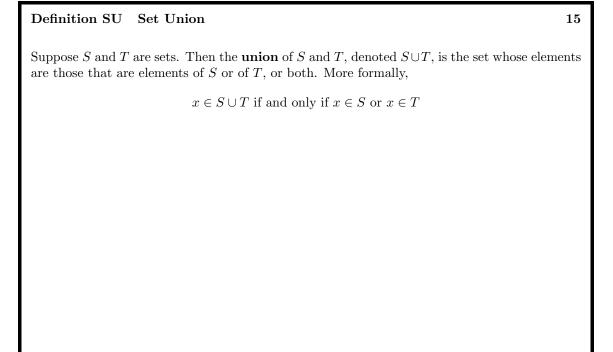


## Definition ES Empty Set

12

The empty set is the set with no elements. Its is denoted by  $\emptyset$ .





#### Definition SI Set Intersection

**16** 

Suppose S and T are sets. Then the **intersection** of S and T, denoted  $S \cap T$ , is the set whose elements are only those that are elements of S and of T. More formally,

 $x \in S \cap T$  if and only if  $x \in S$  and  $x \in T$ 

©2005, 2006 Robert A. Beezer



Suppose S is a set that is a subset of a universal set U. Then the **complement** of S, denoted  $\overline{S}$ , is the set whose elements are those that are elements of U and not elements of S. More formally,

 $x \in \overline{S}$  if and only if  $x \in U$  and  $x \notin S$ 

© 2005, 2006 Robert A. Beezer

#### Definition SLE System of Linear Equations

18

A system of linear equations is a collection of m equations in the variable quantities  $x_1, x_2, x_3, \ldots, x_n$  of the form,

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \dots + a_{1n}x_n = b_1$$

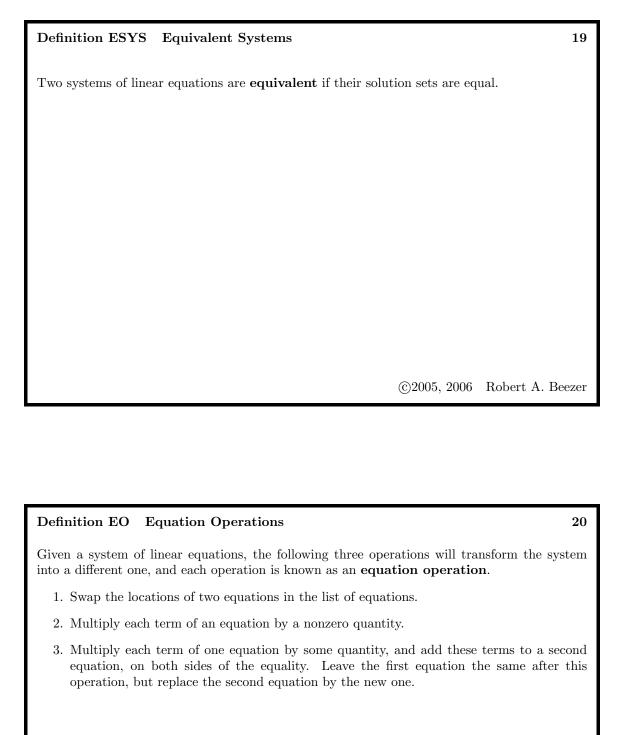
$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \dots + a_{2n}x_n = b_2$$

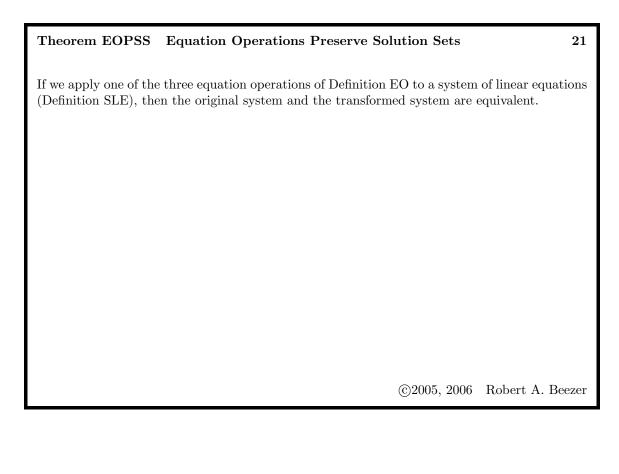
$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \dots + a_{3n}x_n = b_3$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \dots + a_{mn}x_n = b_m$$

where the values of  $a_{ij}$ ,  $b_i$  and  $x_j$  are from the set of complex numbers,  $\mathbb{C}$ .





Definition M Matrix 22

An  $m \times n$  matrix is a rectangular layout of numbers from  $\mathbb{C}$  having m rows and n columns. We will use upper-case Latin letters from the start of the alphabet (A, B, C, ...) to denote matrices and squared-off brackets to delimit the layout. Many use large parentheses instead of brackets — the distinction is not important. Rows of a matrix will be referenced starting at the top and working down (i.e. row 1 is at the top) and columns will be referenced starting from the left (i.e. column 1 is at the left). For a matrix A, the notation  $[A]_{ij}$  will refer to the complex number in row i and column j of A.

A **column vector** of **size** m is an ordered list of m numbers, which is written in order vertically, starting at the top and proceeding to the bottom. At times, we will refer to a column vector as simply a **vector**. Column vectors will be written in bold, usually with lower case Latin letter from the end of the alphabet such as  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w}$ ,  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{z}$ . Some books like to write vectors with arrows, such as  $\vec{u}$ . Writing by hand, some like to put arrows on top of the symbol, or a tilde underneath the symbol, as in u. To refer to the **entry** or **component** that is number i in the list that is the vector  $\mathbf{v}$  we write  $[\mathbf{v}]_i$ .

© 2005, 2006 Robert A. Beezer

#### Definition ZCV Zero Column Vector

24

The **zero vector** of size m is the column vector of size m where each entry is the number zero,

$$\mathbf{0} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

or more compactly,  $[\mathbf{0}]_i = 0$  for  $1 \le i \le m$ .

## Definition CM Coefficient Matrix

For a system of linear equations,

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \dots + a_{2n}x_n = b_2$$

$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \dots + a_{3n}x_n = b_3$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \dots + a_{mn}x_n = b_m$$

the **coefficient matrix** is the  $m \times n$  matrix

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \vdots & & & & \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}$$

©2005, 2006 Robert A. Beezer

#### Definition VOC Vector of Constants

For a system of linear equations,

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \dots + a_{2n}x_n = b_2$$

$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \dots + a_{3n}x_n = b_3$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \dots + a_{mn}x_n = b_m$$

the **vector of constants** is the column vector of size m

$$\mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_m \end{bmatrix}$$

© 2005, 2006 Robert A. Beezer

**25** 

**26** 

#### Definition SV Solution Vector

27

For a system of linear equations,

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \dots + a_{2n}x_n = b_2$$

$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \dots + a_{3n}x_n = b_3$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \dots + a_{mn}x_n = b_m$$

the **solution vector** is the column vector of size n

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

©2005, 2006 Robert A. Beezer

## Definition LSMR Matrix Representation of a Linear System

**28** 

If A is the coefficient matrix of a system of linear equations and  $\mathbf{b}$  is the vector of constants, then we will write  $\mathcal{LS}(A, \mathbf{b})$  as a shorthand expression for the system of linear equations, which we will refer to as the **matrix representation** of the linear system.



Suppose we have a system of m equations in n variables, with coefficient matrix A and vector of constants  $\mathbf{b}$ . Then the **augmented matrix** of the system of equations is the  $m \times (n+1)$  matrix whose first n columns are the columns of A and whose last column (number n+1) is the column vector  $\mathbf{b}$ . This matrix will be written as  $[A \mid \mathbf{b}]$ .

© 2005, 2006 Robert A. Beezer

## Definition RO Row Operations

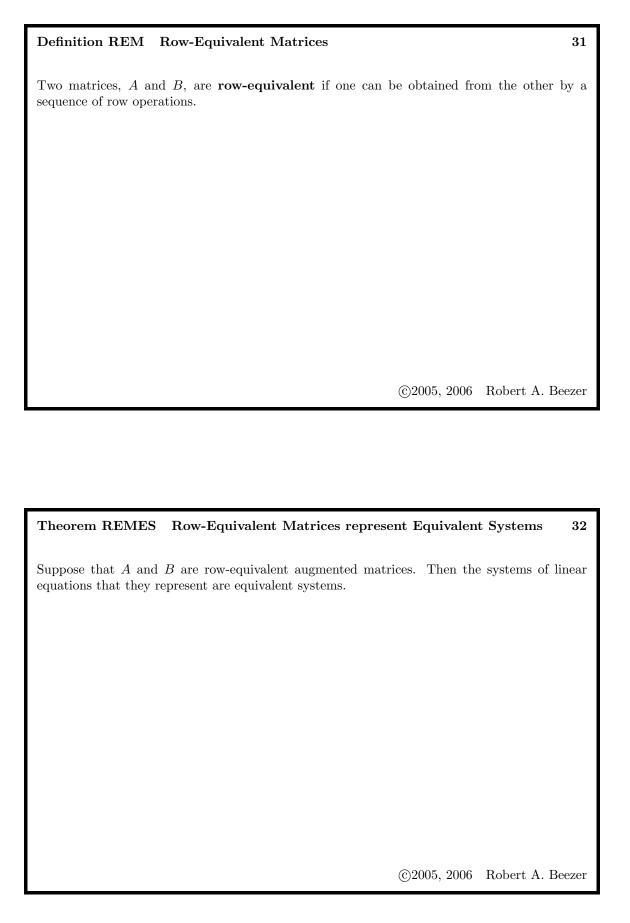
30

The following three operations will transform an  $m \times n$  matrix into a different matrix of the same size, and each is known as a **row operation**.

- 1. Swap the locations of two rows.
- 2. Multiply each entry of a single row by a nonzero quantity.
- 3. Multiply each entry of one row by some quantity, and add these values to the entries in the same columns of a second row. Leave the first row the same after this operation, but replace the second row by the new values.

We will use a symbolic shorthand to describe these row operations:

- 1.  $R_i \leftrightarrow R_j$ : Swap the location of rows i and j.
- 2.  $\alpha R_i$ : Multiply row i by the nonzero scalar  $\alpha$ .
- 3.  $\alpha R_i + R_j$ : Multiply row i by the scalar  $\alpha$  and add to row j.



#### Definition RREF Reduced Row-Echelon Form

33

A matrix is in **reduced row-echelon form** if it meets all of the following conditions:

- 1. A row where every entry is zero lies below any row that contains a nonzero entry.
- 2. The leftmost nonzero entry of a row is equal to 1.
- 3. The leftmost nonzero entry of a row is the only nonzero entry in its column.
- 4. Consider any two different leftmost nonzero entries, one located in row i, column j and the other located in row s, column t. If s > i, then t > j.

A row of only zero entries will be called a **zero row** and the leftmost nonzero entry of a nonzero row will be called a **leading 1**. The number of nonzero rows will be denoted by r.

A column containing a leading 1 will be called a **pivot column**. The set of column indices for all of the pivot columns will be denoted by  $D = \{d_1, d_2, d_3, \ldots, d_r\}$  where  $d_1 < d_2 < d_3 < \cdots < d_r$ , while the columns that are not pivot columns will be denoted as  $F = \{f_1, f_2, f_3, \ldots, f_{n-r}\}$  where  $f_1 < f_2 < f_3 < \cdots < f_{n-r}$ .

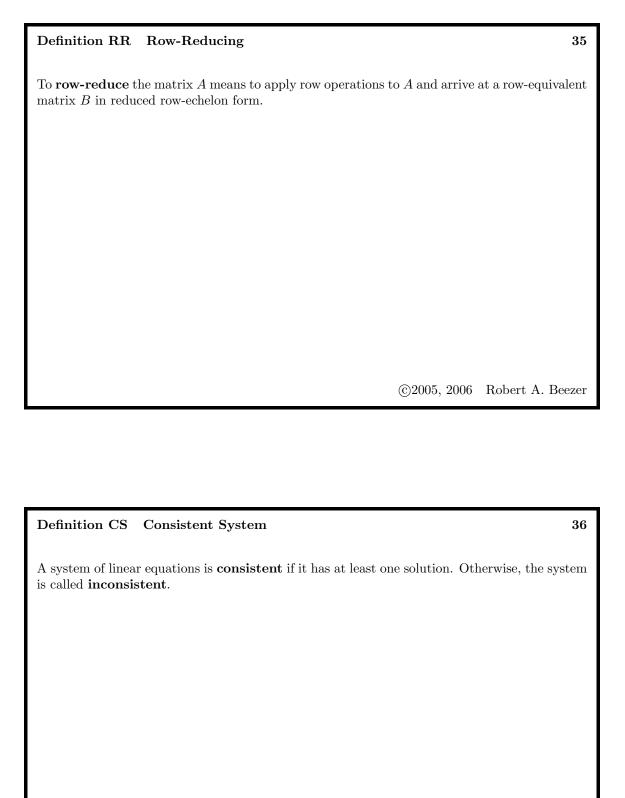
© 2005, 2006 Robert A. Beezer

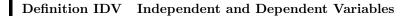
#### Theorem REMEF Row-Equivalent Matrix in Echelon Form

34

Suppose A is a matrix. Then there is a matrix B so that

- 1. A and B are row-equivalent.
- 2. B is in reduced row-echelon form.





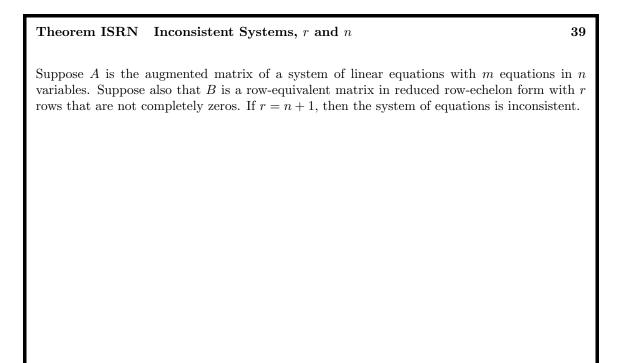
Suppose A is the augmented matrix of a consistent system of linear equations and B is a row-equivalent matrix in reduced row-echelon form. Suppose j is the index of a column of B that contains the leading 1 for some row (i.e. column j is a pivot column), and this column is not the last column. Then the variable  $x_j$  is **dependent**. A variable that is not dependent is called **independent** or **free**.

© 2005, 2006 Robert A. Beezer

#### Theorem RCLS Recognizing Consistency of a Linear System

38

Suppose A is the augmented matrix of a system of linear equations with m equations in n variables. Suppose also that B is a row-equivalent matrix in reduced row-echelon form with r rows that are not zero rows. Then the system of equations is inconsistent if and only if the leading 1 of row r is located in column n+1 of B.

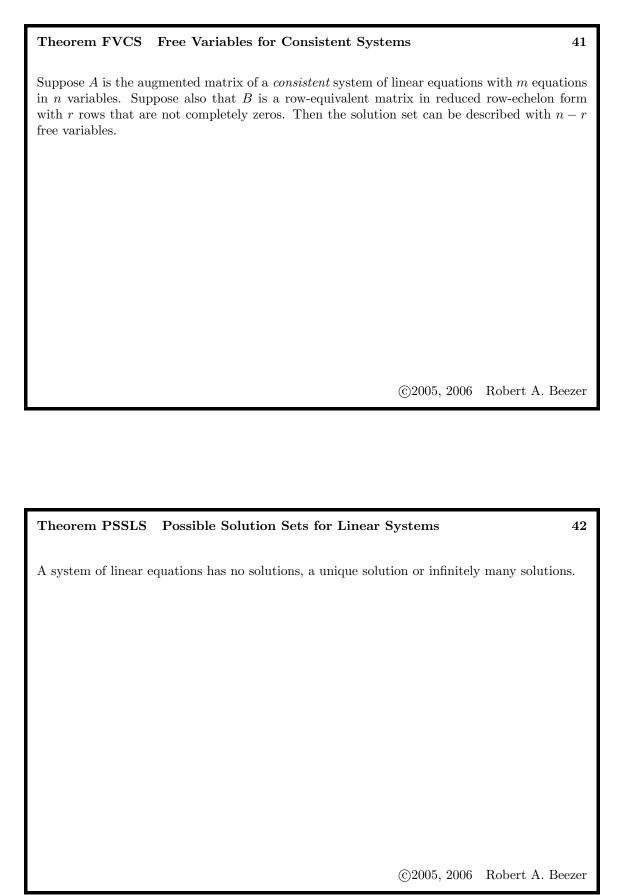


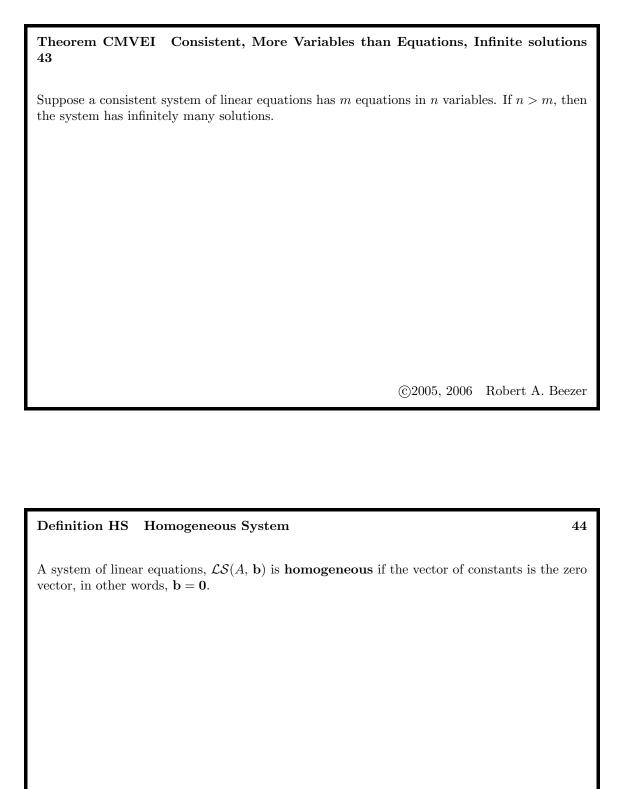
#### Theorem CSRN Consistent Systems, r and n

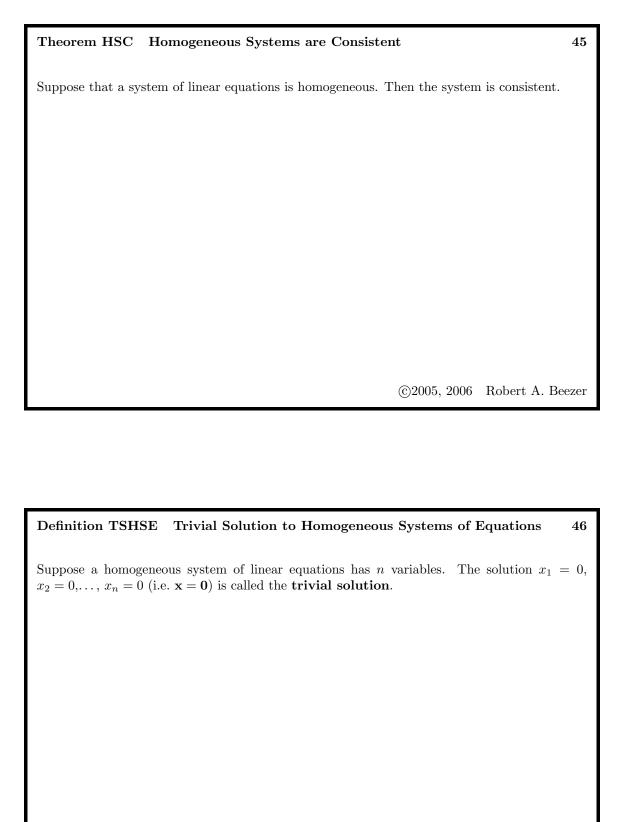
**40** 

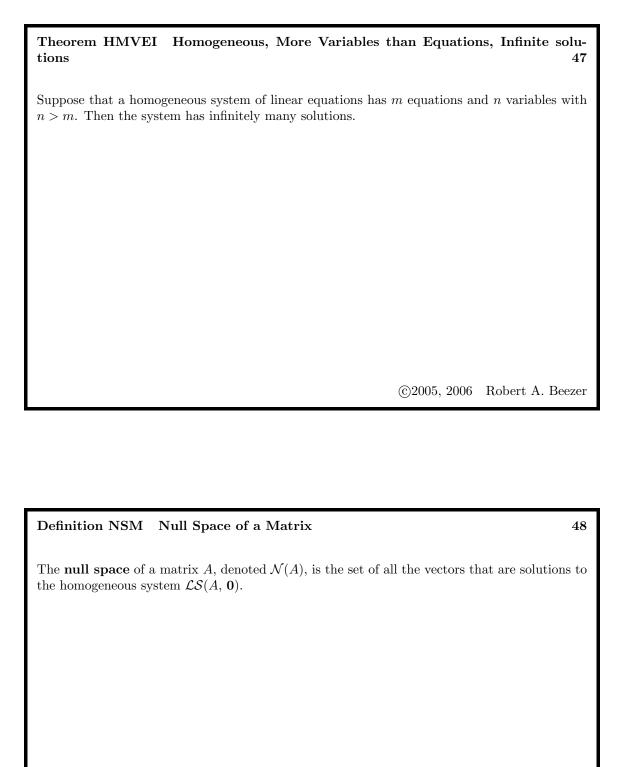
Suppose A is the augmented matrix of a *consistent* system of linear equations with m equations in n variables. Suppose also that B is a row-equivalent matrix in reduced row-echelon form with r rows that are not zero rows. Then  $r \leq n$ . If r = n, then the system has a unique solution, and if r < n, then the system has infinitely many solutions.

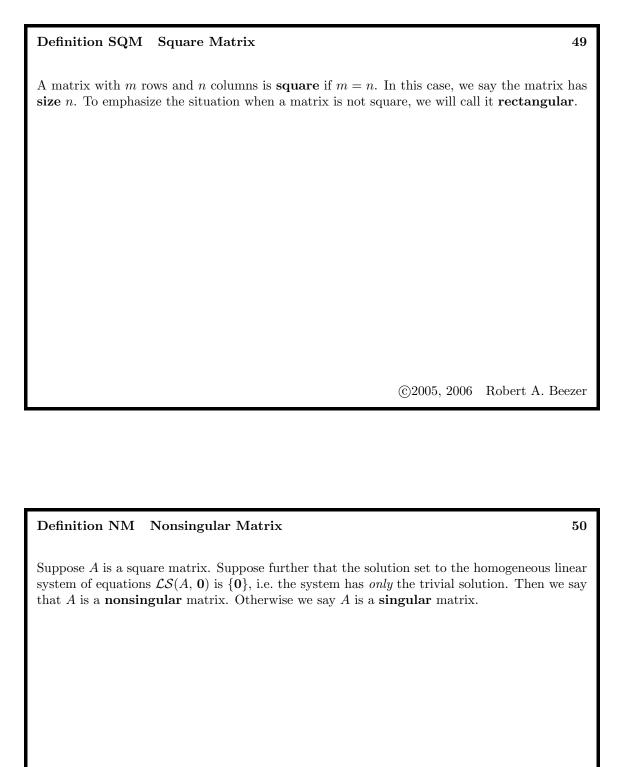
©2005, 2006 Robert A. Beezer

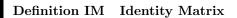












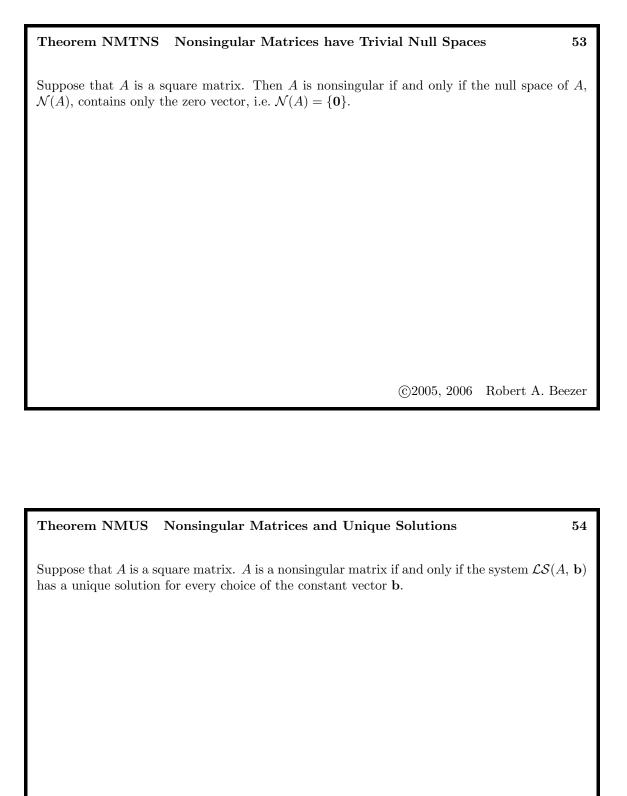
The  $m \times m$  identity matrix,  $I_m$ , is defined by

$$[I_m]_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

©2005, 2006 Robert A. Beezer

## Theorem NMRRI Nonsingular Matrices Row Reduce to the Identity matrix 52

Suppose that A is a square matrix and B is a row-equivalent matrix in reduced row-echelon form. Then A is nonsingular if and only if B is the identity matrix.



Theorem	NME1	Nonsingular	Matrix E	anivalences	Round	1
THEOLEIN	TATATTAT	ronsingulai	Maula L	quivaiences,	itounu	1

Suppose that A is a square matrix. The following are equivalent.

- 1. A is nonsingular.
- $2.\ A$  row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{0\}$ .
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .

©2005, 2006 Robert A. Beezer

## Definition VSCV Vector Space of Column Vectors

**56** 

The vector space  $\mathbb{C}^m$  is the set of all column vectors (Definition CV) of size m with entries from the set of complex numbers,  $\mathbb{C}$ .

## Definition CVE Column Vector Equality

**57** 

Suppose that  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ . Then  $\mathbf{u}$  and  $\mathbf{v}$  are equal, written  $\mathbf{u} = \mathbf{v}$  if

$$[\mathbf{u}]_i = [\mathbf{v}]_i$$

$$1 \le i \le m$$

©2005, 2006 Robert A. Beezer

## Definition CVA Column Vector Addition

 $\mathbf{58}$ 

Suppose that  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ . The **sum** of  $\mathbf{u}$  and  $\mathbf{v}$  is the vector  $\mathbf{u} + \mathbf{v}$  defined by

$$[\mathbf{u} + \mathbf{v}]_i = [\mathbf{u}]_i + [\mathbf{v}]_i$$

$$1 \le i \le m$$

Suppose  $\mathbf{u} \in \mathbb{C}^m$  and  $\alpha \in \mathbb{C}$ , then the scalar multiple of  $\mathbf{u}$  by  $\alpha$  is the vector  $\alpha \mathbf{u}$  defined by

$$\left[\alpha \mathbf{u}\right]_i = \alpha \left[\mathbf{u}\right]_i \qquad \qquad 1 \le i \le m$$

© 2005, 2006 Robert A. Beezer

## Theorem VSPCV Vector Space Properties of Column Vectors

60

Suppose that  $\mathbb{C}^m$  is the set of column vectors of size m (Definition VSCV) with addition and scalar multiplication as defined in Definition CVA and Definition CVSM. Then

- ACC Additive Closure, Column Vectors If  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ , then  $\mathbf{u} + \mathbf{v} \in \mathbb{C}^m$ .
- SCC Scalar Closure, Column Vectors If  $\alpha \in \mathbb{C}$  and  $\mathbf{u} \in \mathbb{C}^m$ , then  $\alpha \mathbf{u} \in \mathbb{C}^m$ .
- CC Commutativity, Column Vectors If  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ , then  $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$ .
- AAC Additive Associativity, Column Vectors If  $\mathbf{u}, \mathbf{v}, \mathbf{w} \in \mathbb{C}^m$ , then  $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$ .
- ZC Zero Vector, Column Vectors There is a vector,  $\mathbf{0}$ , called the zero vector, such that  $\mathbf{u} + \mathbf{0} = \mathbf{u}$  for all  $\mathbf{u} \in \mathbb{C}^m$ .
- AIC Additive Inverses, Column Vectors If  $\mathbf{u} \in \mathbb{C}^m$ , then there exists a vector  $-\mathbf{u} \in \mathbb{C}^m$  so that  $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$ .
- SMAC Scalar Multiplication Associativity, Column Vectors If  $\alpha, \beta \in \mathbb{C}$  and  $\mathbf{u} \in \mathbb{C}^m$ , then  $\alpha(\beta \mathbf{u}) = (\alpha \beta) \mathbf{u}$ .
- DVAC Distributivity across Vector Addition, Column Vectors If  $\alpha \in \mathbb{C}$  and  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ , then  $\alpha(\mathbf{u} + \mathbf{v}) = \alpha \mathbf{u} + \alpha \mathbf{v}$ .
- DSAC Distributivity across Scalar Addition, Column Vectors If  $\alpha, \beta \in \mathbb{C}$  and  $\mathbf{u} \in \mathbb{C}^m$ , then  $(\alpha + \beta)\mathbf{u} = \alpha\mathbf{u} + \beta\mathbf{u}$ .
- OC One Column Vectors If  $u \in \mathbb{C}^m$  then 1u u



62

Given n vectors  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_n$  from  $\mathbb{C}^m$  and n scalars  $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n$ , their **linear combination** is the vector

$$\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 + \cdots + \alpha_n\mathbf{u}_n.$$

© 2005, 2006 Robert A. Beezer

## Theorem SLSLC Solutions to Linear Systems are Linear Combinations

Denote the columns of the  $m \times n$  matrix A as the vectors  $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \ldots, \mathbf{A}_n$ . Then  $\mathbf{x}$  is a solution to the linear system of equations  $\mathcal{LS}(A, \mathbf{b})$  if and only if

$$[\mathbf{x}]_1 \mathbf{A}_1 + [\mathbf{x}]_2 \mathbf{A}_2 + [\mathbf{x}]_3 \mathbf{A}_3 + \dots + [\mathbf{x}]_n \mathbf{A}_n = \mathbf{b}$$

#### Theorem VFSLS Vector Form of Solutions to Linear Systems

Suppose that  $[A \mid \mathbf{b}]$  is the augmented matrix for a consistent linear system  $\mathcal{LS}(A, \mathbf{b})$  of m equations in n variables. Let B be a row-equivalent  $m \times (n+1)$  matrix in reduced row-echelon form. Suppose that B has r nonzero rows, columns without leading 1's with indices  $F = \{f_1, f_2, f_3, \ldots, f_{n-r}, n+1\}$ , and columns with leading 1's (pivot columns) having indices  $D = \{d_1, d_2, d_3, \ldots, d_r\}$ . Define vectors  $\mathbf{c}, \mathbf{u}_j, 1 \le j \le n-r$  of size n by

$$\begin{aligned} \left[\mathbf{c}\right]_i &= \begin{cases} 0 & \text{if } i \in F \\ \left[B\right]_{k,n+1} & \text{if } i \in D, \, i = d_k \end{cases} \\ \left[\mathbf{u}_j\right]_i &= \begin{cases} 1 & \text{if } i \in F, \, i = f_j \\ 0 & \text{if } i \in F, \, i \neq f_j \\ -\left[B\right]_{k,f_j} & \text{if } i \in D, \, i = d_k \end{cases} \end{aligned}$$

Then the set of solutions to the system of equations  $\mathcal{LS}(A, \mathbf{b})$  is

$$S = \left\{ \mathbf{c} + x_{f_1} \mathbf{u}_1 + x_{f_2} \mathbf{u}_2 + x_{f_3} \mathbf{u}_3 + \dots + x_{f_{n-r}} \mathbf{u}_{n-r} \mid x_{f_1}, x_{f_2}, x_{f_3}, \dots, x_{f_{n-r}} \in \mathbb{C} \right\}$$

©2005, 2006 Robert A. Beezer

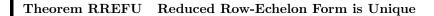
#### Theorem PSPHS Particular Solution Plus Homogeneous Solutions

Suppose that **w** is one solution to the linear system of equations  $\mathcal{LS}(A, b)$ . Then **y** is a solution to  $\mathcal{LS}(A, b)$  if and only if  $\mathbf{y} = \mathbf{w} + \mathbf{z}$  for some vector  $\mathbf{z} \in \mathcal{N}(A)$ .

©2005, 2006 Robert A. Beezer

63

64



Suppose that A is an  $m \times n$  matrix and that B and C are  $m \times n$  matrices that are row-equivalent to A and in reduced row-echelon form. Then B = C.

© 2005, 2006 Robert A. Beezer

#### Definition SSCV Span of a Set of Column Vectors

66

Given a set of vectors  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_p\}$ , their **span**,  $\langle S \rangle$ , is the set of all possible linear combinations of  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_p$ . Symbolically,

$$\langle S \rangle = \{ \alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \dots + \alpha_p \mathbf{u}_p \mid \alpha_i \in \mathbb{C}, \ 1 \le i \le p \}$$
$$= \left\{ \sum_{i=1}^p \alpha_i \mathbf{u}_i \mid \alpha_i \in \mathbb{C}, \ 1 \le i \le p \right\}$$

#### Theorem SSNS Spanning Sets for Null Spaces

67

Suppose that A is an  $m \times n$  matrix, and B is a row-equivalent matrix in reduced row-echelon form with r nonzero rows. Let  $D = \{d_1, d_2, d_3, \ldots, d_r\}$  be the column indices where B has leading 1's (pivot columns) and  $F = \{f_1, f_2, f_3, \ldots, f_{n-r}\}$  be the set of column indices where B does not have leading 1's. Construct the n-r vectors  $\mathbf{z}_j$ ,  $1 \le j \le n-r$  of size n as

$$\left[\mathbf{z}_{j}\right]_{i} = \begin{cases} 1 & \text{if } i \in F, \ i = f_{j} \\ 0 & \text{if } i \in F, \ i \neq f_{j} \\ -\left[B\right]_{k,f_{j}} & \text{if } i \in D, \ i = d_{k} \end{cases}$$

Then the null space of A is given by

$$\mathcal{N}(A) = \langle \{\mathbf{z}_1, \, \mathbf{z}_2, \, \mathbf{z}_3, \, \dots, \, \mathbf{z}_{n-r}\} \rangle.$$

© 2005, 2006 Robert A. Beezer

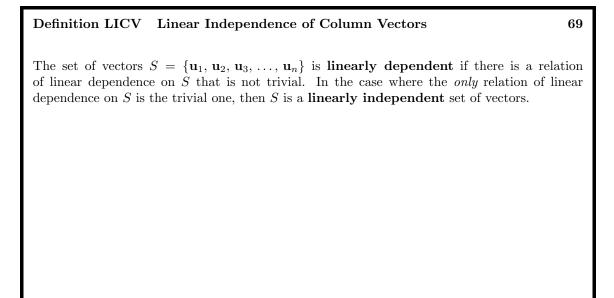
#### Definition RLDCV Relation of Linear Dependence for Column Vectors

68

Given a set of vectors  $S = {\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_n}$ , a true statement of the form

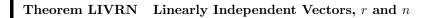
$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \dots + \alpha_n \mathbf{u}_n = \mathbf{0}$$

is a **relation of linear dependence** on S. If this statement is formed in a trivial fashion, i.e.  $\alpha_i = 0, 1 \le i \le n$ , then we say it is the **trivial relation of linear dependence** on S.



## Theorem LIVHS Linearly Independent Vectors and Homogeneous Systems 70

Suppose that A is an  $m \times n$  matrix and  $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \ldots, \mathbf{A}_n\}$  is the set of vectors in  $\mathbb{C}^m$  that are the columns of A. Then S is a linearly independent set if and only if the homogeneous system  $\mathcal{LS}(A, \mathbf{0})$  has a unique solution.



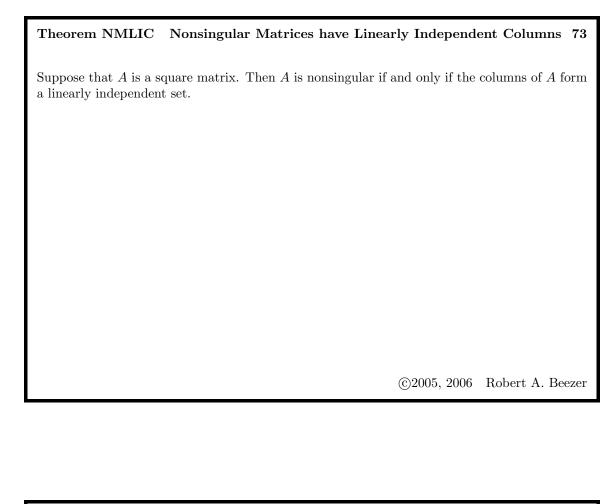
Suppose that A is an  $m \times n$  matrix and  $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$  is the set of vectors in  $\mathbb{C}^m$  that are the columns of A. Let B be a matrix in reduced row-echelon form that is row-equivalent to A and let r denote the number of non-zero rows in B. Then S is linearly independent if and only if n = r.

©2005, 2006 Robert A. Beezer

### Theorem MVSLD More Vectors than Size implies Linear Dependence

72

Suppose that  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is the set of vectors in  $\mathbb{C}^m$ , and that n > m. Then S is a linearly dependent set.



### Theorem NME2 Nonsingular Matrix Equivalences, Round 2

**74** 

Suppose that A is a square matrix. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{0\}$ .
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A form a linearly independent set.

### Theorem BNS Basis for Null Spaces

**75** 

Suppose that A is an  $m \times n$  matrix, and B is a row-equivalent matrix in reduced row-echelon form with r nonzero rows. Let  $D = \{d_1, d_2, d_3, \ldots, d_r\}$  and  $F = \{f_1, f_2, f_3, \ldots, f_{n-r}\}$  be the sets of column indices where B does and does not (respectively) have leading 1's. Construct the n-r vectors  $\mathbf{z}_j$ ,  $1 \le j \le n-r$  of size n as

$$\left[\mathbf{z}_{j}\right]_{i} = \begin{cases} 1 & \text{if } i \in F, \ i = f_{j} \\ 0 & \text{if } i \in F, \ i \neq f_{j} \\ -\left[B\right]_{k,f_{j}} & \text{if } i \in D, \ i = d_{k} \end{cases}$$

Define the set  $S = \{\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \dots, \mathbf{z}_{n-r}\}$ . Then

- 1.  $\mathcal{N}(A) = \langle S \rangle$ .
- 2. S is a linearly independent set.

© 2005, 2006 Robert A. Beezer

#### Theorem DLDS Dependency in Linearly Dependent Sets

76

Suppose that  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is a set of vectors. Then S is a linearly dependent set if and only if there is an index  $t, 1 \le t \le n$  such that  $\mathbf{u}_t$  is a linear combination of the vectors  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_{t-1}, \mathbf{u}_{t+1}, \dots, \mathbf{u}_n$ .

## Theorem BS Basis of a Span

77

Suppose that  $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$  is a set of column vectors. Define  $W = \langle S \rangle$  and let A be the matrix whose columns are the vectors from S. Let B be the reduced row-echelon form of A, with  $D = \{d_1, d_2, d_3, \dots, d_r\}$  the set of column indices corresponding to the pivot columns of B. Then

- 1.  $T = \{\mathbf{v}_{d_1}, \mathbf{v}_{d_2}, \mathbf{v}_{d_3}, \dots \mathbf{v}_{d_r}\}$  is a linearly independent set.
- 2.  $W = \langle T \rangle$ .

© 2005, 2006 Robert A. Beezer

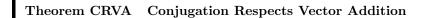
### Definition CCCV Complex Conjugate of a Column Vector

**78** 

Suppose that **u** is a vector from  $\mathbb{C}^m$ . Then the conjugate of the vector,  $\overline{\mathbf{u}}$ , is defined by

$$[\overline{\mathbf{u}}]_i = \overline{[\mathbf{u}]_i}$$

$$1 \leq i \leq m$$



Suppose  $\mathbf{x}$  and  $\mathbf{y}$  are two vectors from  $\mathbb{C}^m$ . Then

$$\overline{\mathbf{x}+\mathbf{y}}=\overline{\mathbf{x}}+\overline{\mathbf{y}}$$

©2005, 2006 Robert A. Beezer

## Theorem CRSM Conjugation Respects Vector Scalar Multiplication

80

Suppose **x** is a vector from  $\mathbb{C}^m$ , and  $\alpha \in \mathbb{C}$  is a scalar. Then

$$\overline{\alpha}\overline{\mathbf{x}} = \overline{\alpha}\,\overline{\mathbf{x}}$$

## Definition IP Inner Product

81

Given the vectors  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$  the **inner product** of  $\mathbf{u}$  and  $\mathbf{v}$  is the scalar quantity in  $\mathbb{C}$ ,

$$\langle \mathbf{u}, \mathbf{v} \rangle = \left[ \mathbf{u} \right]_1 \overline{\left[ \mathbf{v} \right]_1} + \left[ \mathbf{u} \right]_2 \overline{\left[ \mathbf{v} \right]_2} + \left[ \mathbf{u} \right]_3 \overline{\left[ \mathbf{v} \right]_3} + \dots + \left[ \mathbf{u} \right]_m \overline{\left[ \mathbf{v} \right]_m} = \sum_{i=1}^m \left[ \mathbf{u} \right]_i \overline{\left[ \mathbf{v} \right]_i}$$

©2005, 2006 Robert A. Beezer

#### Theorem IPVA Inner Product and Vector Addition

82

Suppose  $\mathbf{u}, \mathbf{v}, \mathbf{w} \in \mathbb{C}^m$ . Then

1. 
$$\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{w} \rangle + \langle \mathbf{v}, \mathbf{w} \rangle$$

2. 
$$\langle \mathbf{u}, \mathbf{v} + \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{v} \rangle + \langle \mathbf{u}, \mathbf{w} \rangle$$

## Theorem IPSM Inner Product and Scalar Multiplication

83

Suppose  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$  and  $\alpha \in \mathbb{C}$ . Then

- 1.  $\langle \alpha \mathbf{u}, \mathbf{v} \rangle = \alpha \langle \mathbf{u}, \mathbf{v} \rangle$
- 2.  $\langle \mathbf{u}, \, \alpha \mathbf{v} \rangle = \overline{\alpha} \, \langle \mathbf{u}, \, \mathbf{v} \rangle$

©2005, 2006 Robert A. Beezer

## Theorem IPAC Inner Product is Anti-Commutative

84

Suppose that **u** and **v** are vectors in  $\mathbb{C}^m$ . Then  $\langle \mathbf{u}, \mathbf{v} \rangle = \overline{\langle \mathbf{v}, \mathbf{u} \rangle}$ .

## Definition NV Norm of a Vector

85

The  $\bf{norm}$  of the vector  $\bf{u}$  is the scalar quantity in  $\mathbb C$ 

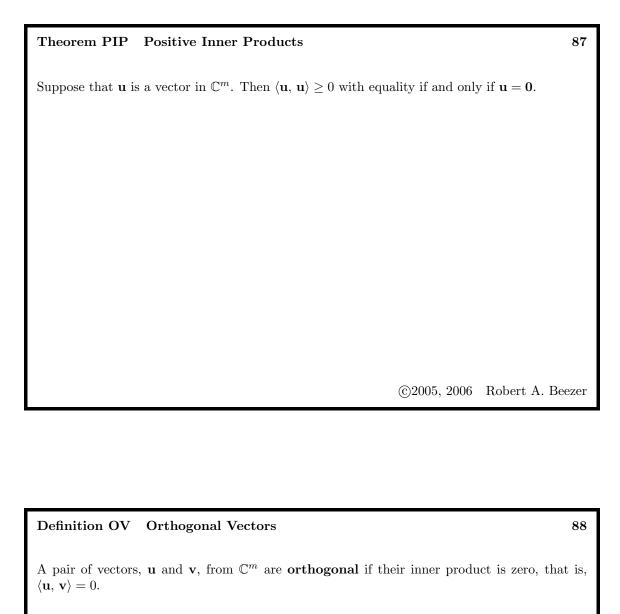
$$\|\mathbf{u}\| = \sqrt{|[\mathbf{u}]_1|^2 + |[\mathbf{u}]_2|^2 + |[\mathbf{u}]_3|^2 + \dots + |[\mathbf{u}]_m|^2} = \sqrt{\sum_{i=1}^m |[\mathbf{u}]_i|^2}$$

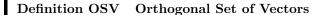
©2005, 2006 Robert A. Beezer

#### Theorem IPN Inner Products and Norms

**86** 

Suppose that **u** is a vector in  $\mathbb{C}^m$ . Then  $\|\mathbf{u}\|^2 = \langle \mathbf{u}, \mathbf{u} \rangle$ .





Suppose that  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is a set of vectors from  $\mathbb{C}^m$ . Then the set S is **orthogonal** if every pair of different vectors from S is orthogonal, that is  $\langle \mathbf{u}_i, \mathbf{u}_j \rangle = 0$  whenever  $i \neq j$ .

©2005, 2006 Robert A. Beezer

### Theorem OSLI Orthogonal Sets are Linearly Independent

90

Suppose that  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is an orthogonal set of nonzero vectors. Then S is linearly independent.

### Theorem GSP Gram-Schmidt Procedure

t set of vectors in  $\mathbb{C}^m$  Define

91

Suppose that  $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_p\}$  is a linearly independent set of vectors in  $\mathbb{C}^m$ . Define the vectors  $\mathbf{u}_i$ ,  $1 \le i \le p$  by

$$\mathbf{u}_i = \mathbf{v}_i - \frac{\langle \mathbf{v}_i, \, \mathbf{u}_1 \rangle}{\langle \mathbf{u}_1, \, \mathbf{u}_1 \rangle} \mathbf{u}_1 - \frac{\langle \mathbf{v}_i, \, \mathbf{u}_2 \rangle}{\langle \mathbf{u}_2, \, \mathbf{u}_2 \rangle} \mathbf{u}_2 - \frac{\langle \mathbf{v}_i, \, \mathbf{u}_3 \rangle}{\langle \mathbf{u}_3, \, \mathbf{u}_3 \rangle} \mathbf{u}_3 - \dots - \frac{\langle \mathbf{v}_i, \, \mathbf{u}_{i-1} \rangle}{\langle \mathbf{u}_{i-1}, \, \mathbf{u}_{i-1} \rangle} \mathbf{u}_{i-1}$$

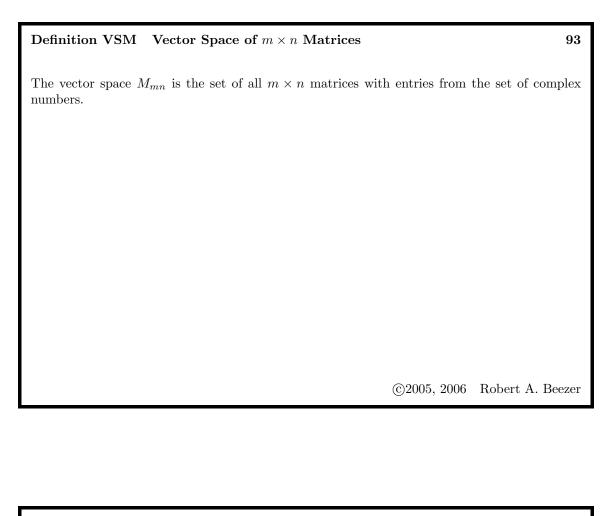
Then if  $T = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_p\}$ , then T is an orthogonal set of non-zero vectors, and  $\langle T \rangle = \langle S \rangle$ .

© 2005, 2006 Robert A. Beezer

#### Definition ONS OrthoNormal Set

92

Suppose  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is an orthogonal set of vectors such that  $\|\mathbf{u}_i\| = 1$  for all  $1 \le i \le n$ . Then S is an **orthonormal** set of vectors.



# Definition ME Matrix Equality

94

The  $m \times n$  matrices A and B are **equal**, written A = B provided  $[A]_{ij} = [B]_{ij}$  for all  $1 \le i \le m$ ,  $1 \le j \le n$ .

## Definition MA Matrix Addition

95

Given the  $m \times n$  matrices A and B, define the **sum** of A and B as an  $m \times n$  matrix, written A + B, according to

$$[A + B]_{ij} = [A]_{ij} + [B]_{ij}$$

$$1 \le i \le m, \ 1 \le j \le n$$

©2005, 2006 Robert A. Beezer

## Definition MSM Matrix Scalar Multiplication

96

Given the  $m \times n$  matrix A and the scalar  $\alpha \in \mathbb{C}$ , the scalar multiple of A is an  $m \times n$  matrix, written  $\alpha A$  and defined according to

$$[\alpha A]_{ij} = \alpha [A]_{ij}$$

$$1 \le i \le m, \ 1 \le j \le n$$

#### Theorem VSPM Vector Space Properties of Matrices

97

Suppose that  $M_{mn}$  is the set of all  $m \times n$  matrices (Definition VSM) with addition and scalar multiplication as defined in Definition MA and Definition MSM. Then

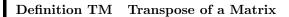
- ACM Additive Closure, Matrices If  $A, B \in M_{mn}$ , then  $A + B \in M_{mn}$ .
- SCM Scalar Closure, Matrices If  $\alpha \in \mathbb{C}$  and  $A \in M_{mn}$ , then  $\alpha A \in M_{mn}$ .
- CM Commutativity, Matrices If  $A, B \in M_{mn}$ , then A + B = B + A.
- AAM Additive Associativity, Matrices If  $A, B, C \in M_{mn}$ , then A + (B + C) = (A + B) + C.
- **ZM Zero Vector, Matrices** There is a matrix,  $\mathcal{O}$ , called the **zero matrix**, such that  $A + \mathcal{O} = A$  for all  $A \in M_{mn}$ .
- AIM Additive Inverses, Matrices If  $A \in M_{mn}$ , then there exists a matrix  $-A \in M_{mn}$  so that  $A + (-A) = \mathcal{O}$ .
- SMAM Scalar Multiplication Associativity, Matrices If  $\alpha$ ,  $\beta \in \mathbb{C}$  and  $A \in M_{mn}$ , then  $\alpha(\beta A) = (\alpha \beta)A$ .
- DMAM Distributivity across Matrix Addition, Matrices If  $\alpha \in \mathbb{C}$  and  $A, B \in M_{mn}$ , then  $\alpha(A+B) = \alpha A + \alpha B$ .
- DSAM Distributivity across Scalar Addition, Matrices If  $\alpha, \beta \in \mathbb{C}$  and  $A \in M_{mn}$ , then  $(\alpha + \beta)A = \alpha A + \beta A$ .
- OM One Matrices If  $A \subset M$  then 1A A

©2005, 2006 Robert A. Beezer

#### Definition ZM Zero Matrix

98

The  $m \times n$  zero matrix is written as  $\mathcal{O} = \mathcal{O}_{m \times n}$  and defined by  $[\mathcal{O}]_{ij} = 0$ , for all  $1 \leq i \leq m$ ,  $1 \leq j \leq n$ .



Given an  $m \times n$  matrix A, its **transpose** is the  $n \times m$  matrix  $A^t$  given by

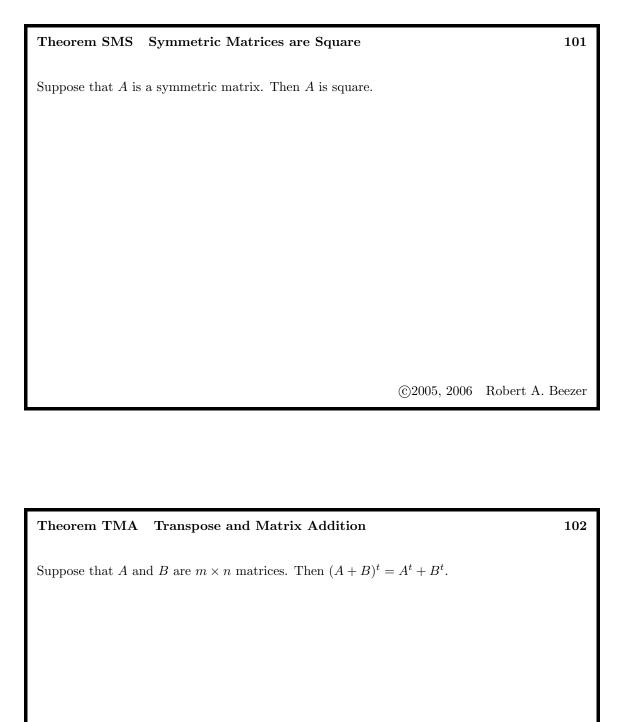
$$\left[A^t\right]_{ij} = \left[A\right]_{ji}, \quad 1 \le i \le n, \, 1 \le j \le m.$$

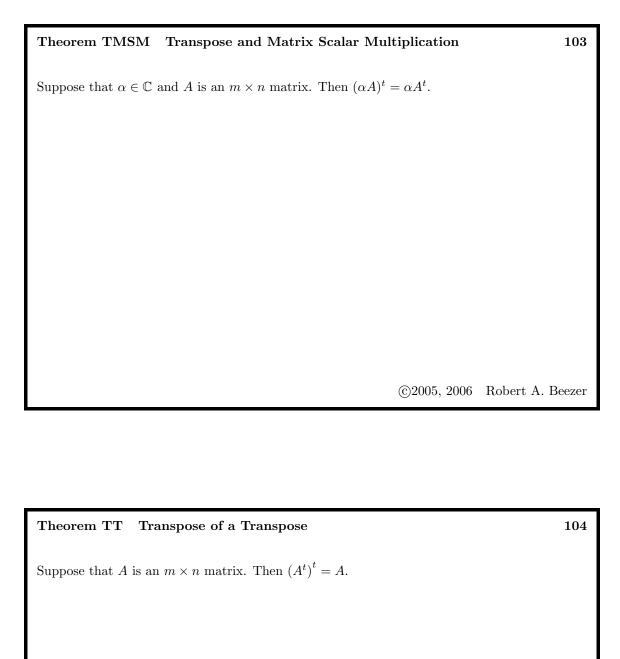
©2005, 2006 Robert A. Beezer

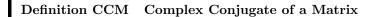
## Definition SYM Symmetric Matrix

100

The matrix A is **symmetric** if  $A = A^t$ .







Suppose A is an  $m \times n$  matrix. Then the **conjugate** of A, written  $\overline{A}$  is an  $m \times n$  matrix defined by

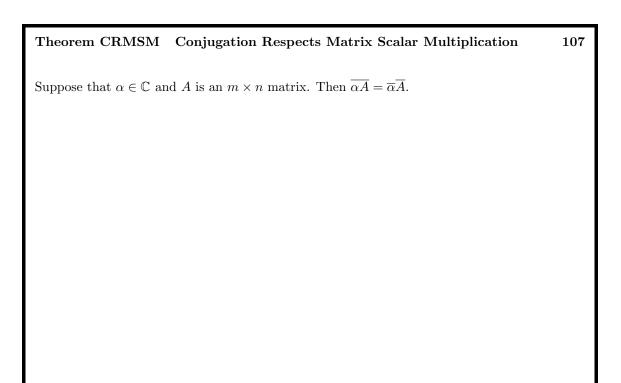
$$\left[\overline{A}\right]_{ij} = \overline{[A]_{ij}}$$

©2005, 2006 Robert A. Beezer

# Theorem CRMA Conjugation Respects Matrix Addition

106

Suppose that A and B are  $m \times n$  matrices. Then  $\overline{A+B} = \overline{A} + \overline{B}$ .



# Theorem CCM Conjugate of the Conjugate of a Matrix

108

Suppose that A is an  $m \times n$  matrix. Then  $\overline{\overline{(A)}} = A$ .

©2005, 2006 Robert A. Beezer



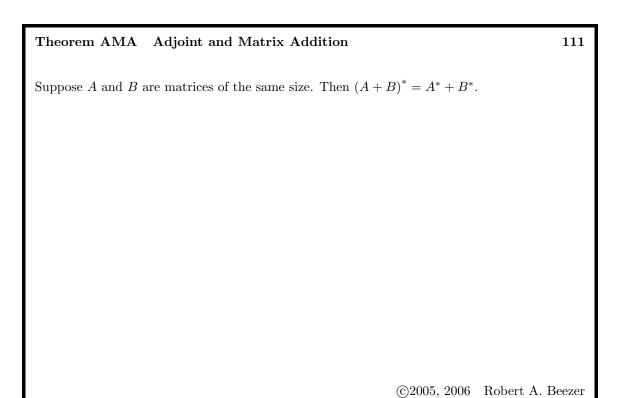
Suppose that A is an  $m \times n$  matrix. Then  $\overline{(A^t)} = \left(\overline{A}\right)^t$ .

©2005, 2006 Robert A. Beezer

## Definition A Adjoint

110

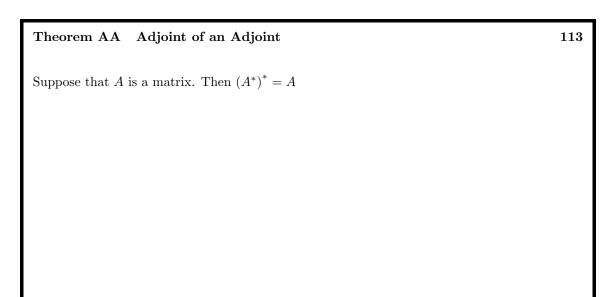
If A is a square matrix, then its **adjoint** is  $A^* = \left(\overline{A}\right)^t$ .



# Theorem AMSM Adjoint and Matrix Scalar Multiplication

112

Suppose  $\alpha \in \mathbb{C}$  is a scalar and A is a matrix. Then  $(\alpha A)^* = \overline{\alpha} A^*$ .

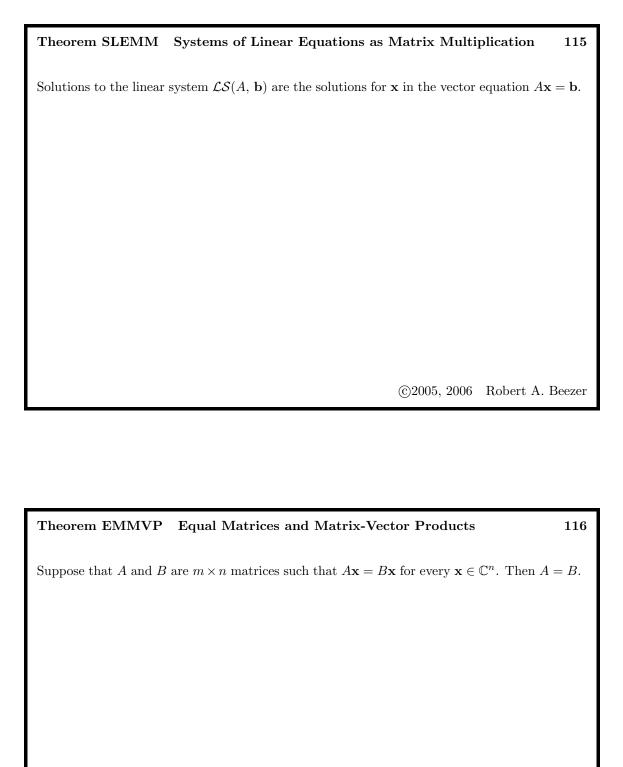


#### Definition MVP Matrix-Vector Product

114

Suppose A is an  $m \times n$  matrix with columns  $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \ldots, \mathbf{A}_n$  and  $\mathbf{u}$  is a vector of size n. Then the **matrix-vector product** of A with  $\mathbf{u}$  is the linear combination

$$A\mathbf{u} = [\mathbf{u}]_1 \mathbf{A}_1 + [\mathbf{u}]_2 \mathbf{A}_2 + [\mathbf{u}]_3 \mathbf{A}_3 + \dots + [\mathbf{u}]_n \mathbf{A}_n$$



#### Definition MM Matrix Multiplication

117

Suppose A is an  $m \times n$  matrix and B is an  $n \times p$  matrix with columns  $\mathbf{B}_1, \mathbf{B}_2, \mathbf{B}_3, \ldots, \mathbf{B}_p$ . Then the **matrix product** of A with B is the  $m \times p$  matrix where column i is the matrix-vector product  $A\mathbf{B}_i$ . Symbolically,

$$AB = A [\mathbf{B}_1 | \mathbf{B}_2 | \mathbf{B}_3 | \dots | \mathbf{B}_p] = [A\mathbf{B}_1 | A\mathbf{B}_2 | A\mathbf{B}_3 | \dots | A\mathbf{B}_p].$$

© 2005, 2006 Robert A. Beezer

#### Theorem EMP Entries of Matrix Products

118

Suppose A is an  $m \times n$  matrix and B =is an  $n \times p$  matrix. Then for  $1 \le i \le m, \ 1 \le j \le p$ , the individual entries of AB are given by

$$[AB]_{ij} = [A]_{i1} [B]_{1j} + [A]_{i2} [B]_{2j} + [A]_{i3} [B]_{3j} + \dots + [A]_{in} [B]_{nj}$$
$$= \sum_{k=1}^{n} [A]_{ik} [B]_{kj}$$

## Theorem MMZM Matrix Multiplication and the Zero Matrix

119

Suppose A is an  $m \times n$  matrix. Then

- 1.  $A\mathcal{O}_{n\times p} = \mathcal{O}_{m\times p}$ 2.  $\mathcal{O}_{p\times m}A = \mathcal{O}_{p\times n}$

©2005, 2006 Robert A. Beezer

### Theorem MMIM Matrix Multiplication and Identity Matrix

120

Suppose A is an  $m \times n$  matrix. Then

- 1.  $AI_n = A$
- $2. \quad I_m A = A$

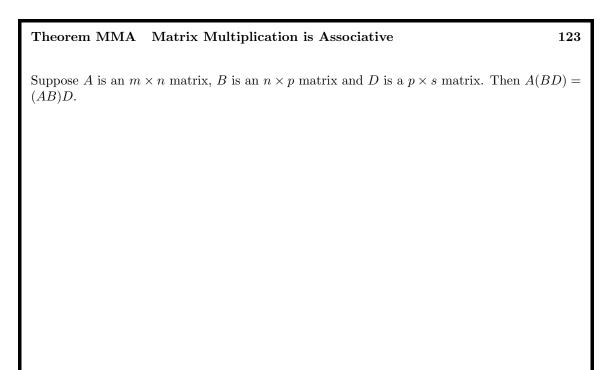
Suppose A is an  $m \times n$  matrix and B and C are  $n \times p$  matrices and D is a  $p \times s$  matrix. Then

- $1. \quad A(B+C) = AB + AC$
- $2. \quad (B+C)D = BD + CD$

©2005, 2006 Robert A. Beezer

### Theorem MMSMM Matrix Multiplication and Scalar Matrix Multiplication 122

Suppose A is an  $m \times n$  matrix and B is an  $n \times p$  matrix. Let  $\alpha$  be a scalar. Then  $\alpha(AB) = (\alpha A)B = A(\alpha B)$ .



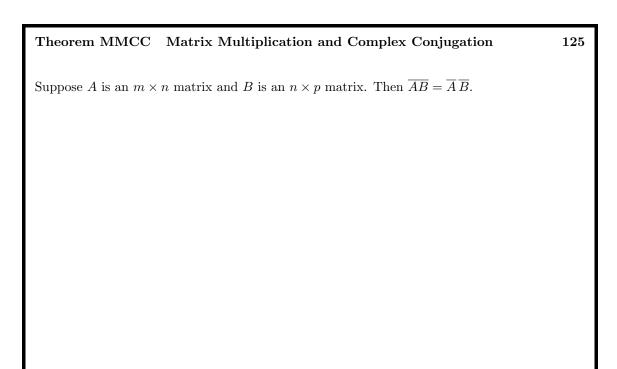
# Theorem MMIP Matrix Multiplication and Inner Products

124

If we consider the vectors  $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$  as  $m \times 1$  matrices then

$$\langle \mathbf{u}, \, \mathbf{v} \rangle = \mathbf{u}^t \overline{\mathbf{v}}$$

©2005, 2006 Robert A. Beezer

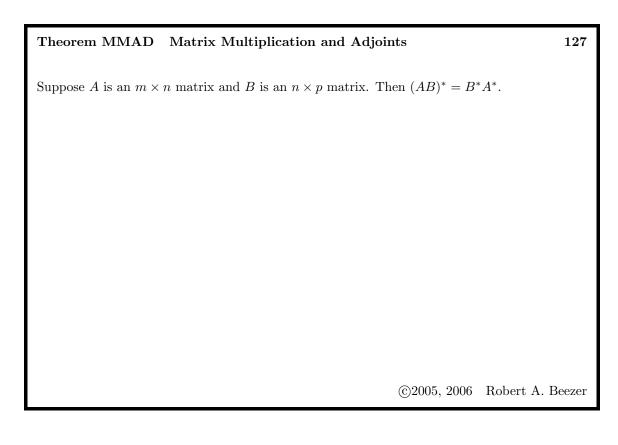


## Theorem MMT Matrix Multiplication and Transposes

126

Suppose A is an  $m \times n$  matrix and B is an  $n \times p$  matrix. Then  $(AB)^t = B^t A^t$ .

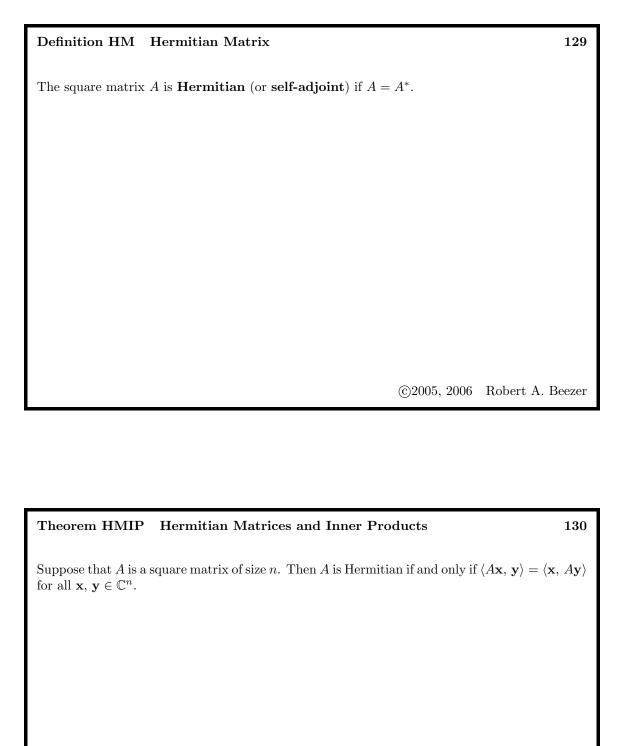
©2005, 2006 Robert A. Beezer

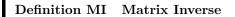


### Theorem AIP Adjoint and Inner Product

128

Suppose that A is an  $m \times n$  matrix and  $\mathbf{x} \in \mathbb{C}^n$ ,  $\mathbf{y} \in \mathbb{C}^m$ . Then  $\langle A\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, A^*\mathbf{y} \rangle$ .





Suppose A and B are square matrices of size n such that  $AB = I_n$  and  $BA = I_n$ . Then A is **invertible** and B is the **inverse** of A. In this situation, we write  $B = A^{-1}$ .

©2005, 2006 Robert A. Beezer

#### Definition SUV Standard Unit Vectors

132

Let  $\mathbf{e}_j \in \mathbb{C}^m$  denote the column vector that is column j of the  $m \times m$  identity matrix  $I_m$ . Then the set

$$\{\mathbf{e}_1, \, \mathbf{e}_2, \, \mathbf{e}_3, \, \dots, \, \mathbf{e}_m\} = \{\, \mathbf{e}_j \mid 1 \le j \le m\}$$

is the set of standard unit vectors in  $\mathbb{C}^m$ .

#### Theorem TTMI Two-by-Two Matrix Inverse

133

Suppose

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Then A is invertible if and only if  $ad - bc \neq 0$ . When A is invertible, we have

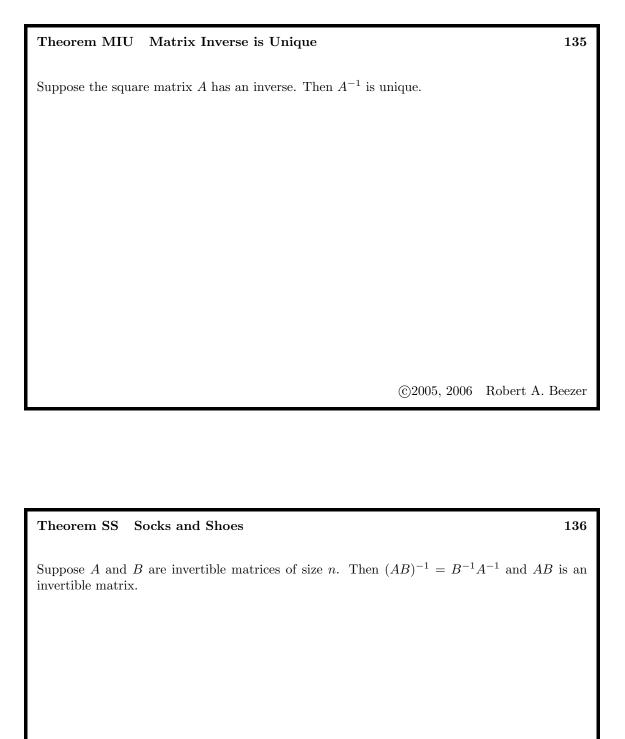
$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}.$$

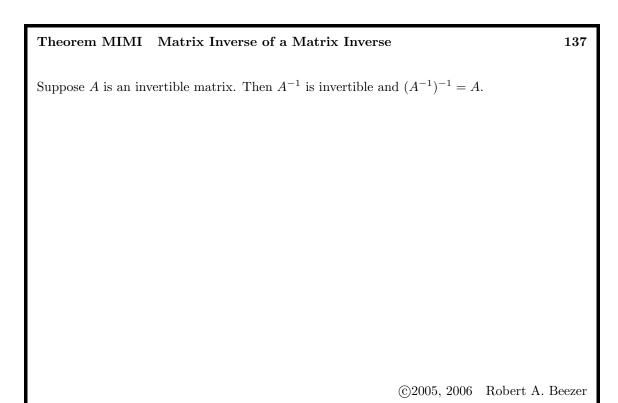
© 2005, 2006 Robert A. Beezer

### Theorem CINM Computing the Inverse of a Nonsingular Matrix

134

Suppose A is a nonsingular square matrix of size n. Create the  $n \times 2n$  matrix M by placing the  $n \times n$  identity matrix  $I_n$  to the right of the matrix A. Let N be a matrix that is row-equivalent to M and in reduced row-echelon form. Finally, let J be the matrix formed from the final n columns of N. Then  $AJ = I_n$ .

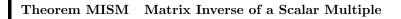




# Theorem MIT Matrix Inverse of a Transpose

138

Suppose A is an invertible matrix. Then  $A^t$  is invertible and  $(A^t)^{-1} = (A^{-1})^t$ .



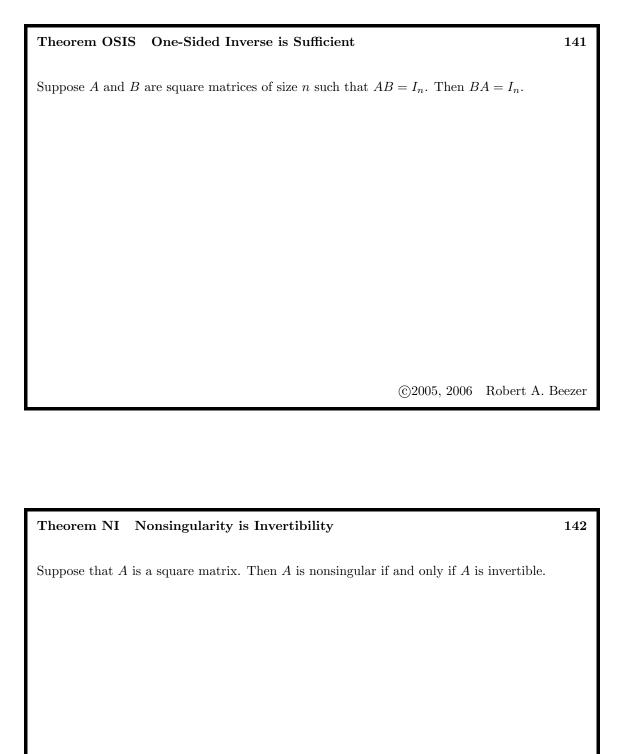
Suppose A is an invertible matrix and  $\alpha$  is a nonzero scalar. Then  $(\alpha A)^{-1} = \frac{1}{\alpha}A^{-1}$  and  $\alpha A$  is invertible.

©2005, 2006 Robert A. Beezer

### Theorem NPNT Nonsingular Product has Nonsingular Terms

140

Suppose that A and B are square matrices of size n and the product AB is nonsingular. Then A and B are both nonsingular.



## Theorem NME3 Nonsingular Matrix Equivalences, Round 3

143

Suppose that A is a square matrix of size n. The following are equivalent.

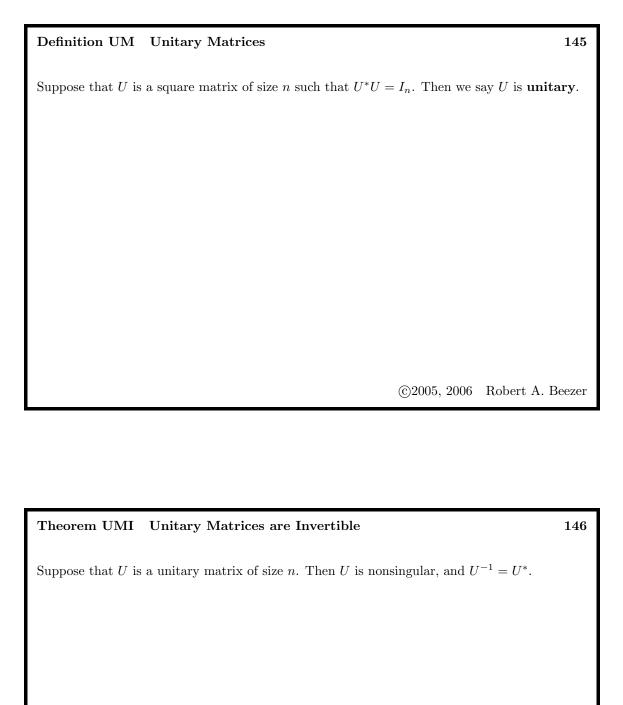
- 1. A is nonsingular.
- $2.\ A$  row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{0\}$ .
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.

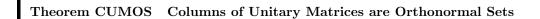
©2005, 2006 Robert A. Beezer

#### Theorem SNCM Solution with Nonsingular Coefficient Matrix

144

Suppose that A is nonsingular. Then the unique solution to  $\mathcal{LS}(A, \mathbf{b})$  is  $A^{-1}\mathbf{b}$ .





Suppose that A is a square matrix of size n with columns  $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$ . Then A is a unitary matrix if and only if S is an orthonormal set.

©2005, 2006 Robert A. Beezer

# Theorem UMPIP Unitary Matrices Preserve Inner Products

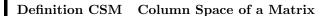
148

Suppose that U is a unitary matrix of size n and  $\mathbf{u}$  and  $\mathbf{v}$  are two vectors from  $\mathbb{C}^n$ . Then

$$\langle U\mathbf{u}, U\mathbf{v} \rangle = \langle \mathbf{u}, \mathbf{v} \rangle$$

and

$$||U\mathbf{v}|| = ||\mathbf{v}||$$



Suppose that A is an  $m \times n$  matrix with columns  $\{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \ldots, \mathbf{A}_n\}$ . Then the **column space** of A, written  $\mathcal{C}(A)$ , is the subset of  $\mathbb{C}^m$  containing all linear combinations of the columns of A,

$$\mathcal{C}(A) = \langle \{\mathbf{A}_1, \, \mathbf{A}_2, \, \mathbf{A}_3, \, \dots, \, \mathbf{A}_n \} \rangle$$

© 2005, 2006 Robert A. Beezer

# Theorem CSCS Column Spaces and Consistent Systems

**150** 

Suppose A is an  $m \times n$  matrix and **b** is a vector of size m. Then  $\mathbf{b} \in \mathcal{C}(A)$  if and only if  $\mathcal{LS}(A, \mathbf{b})$  is consistent.

# Theorem BCS Basis of the Column Space

151

Suppose that A is an  $m \times n$  matrix with columns  $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \ldots, \mathbf{A}_n$ , and B is a row-equivalent matrix in reduced row-echelon form with r nonzero rows. Let  $D = \{d_1, d_2, d_3, \ldots, d_r\}$  be the set of column indices where B has leading 1's. Let  $T = \{\mathbf{A}_{d_1}, \mathbf{A}_{d_2}, \mathbf{A}_{d_3}, \ldots, \mathbf{A}_{d_r}\}$ . Then

- 1. T is a linearly independent set.
- 2.  $C(A) = \langle T \rangle$ .

© 2005, 2006 Robert A. Beezer

# Theorem CSNM Column Space of a Nonsingular Matrix

152

Suppose A is a square matrix of size n. Then A is nonsingular if and only if  $\mathcal{C}(A) = \mathbb{C}^n$ .

#### Theorem NME4 Nonsingular Matrix Equivalences, Round 4

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .

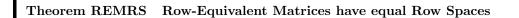
© 2005, 2006 Robert A. Beezer

# Definition RSM Row Space of a Matrix

154

153

Suppose A is an  $m \times n$  matrix. Then the **row space** of A,  $\mathcal{R}(A)$ , is the column space of  $A^t$ , i.e.  $\mathcal{R}(A) = \mathcal{C}(A^t)$ .



Suppose A and B are row-equivalent matrices. Then  $\mathcal{R}(A) = \mathcal{R}(B)$ .

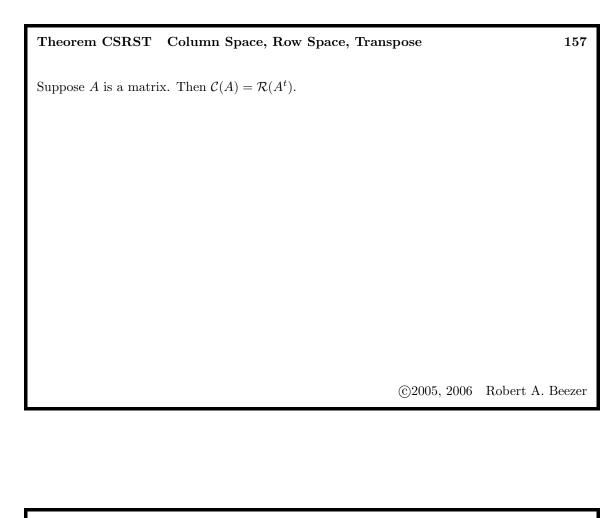
©2005, 2006 Robert A. Beezer

# Theorem BRS Basis for the Row Space

156

Suppose that A is a matrix and B is a row-equivalent matrix in reduced row-echelon form. Let S be the set of nonzero columns of  $B^t$ . Then

- 1.  $\mathcal{R}(A) = \langle S \rangle$ .
- $2.\ S$  is a linearly independent set.



# Definition LNS Left Null Space

158

Suppose A is an  $m \times n$  matrix. Then the **left null space** is defined as  $\mathcal{L}(A) = \mathcal{N}(A^t) \subseteq \mathbb{C}^m$ .

Suppose A is an  $m \times n$  matrix. Add m new columns to A that together equal an  $m \times m$  identity matrix to form an  $m \times (n+m)$  matrix M. Use row operations to bring M to reduced row-echelon form and call the result N. N is the **extended reduced row-echelon form** of A, and we will standardize on names for five submatrices (B, C, J, K, L) of N.

Let B denote the  $m \times n$  matrix formed from the first n columns of N and let J denote the  $m \times m$  matrix formed from the last m columns of N. Suppose that B has r nonzero rows. Further partition N by letting C denote the  $r \times n$  matrix formed from all of the non-zero rows of B. Let K be the  $r \times m$  matrix formed from the first r rows of J, while L will be the  $(m-r) \times m$  matrix formed from the bottom m-r rows of J. Pictorially,

$$M = [A|I_m] \xrightarrow{\text{RREF}} N = [B|J] = \begin{bmatrix} C & K \\ \hline 0 & L \end{bmatrix}$$

© 2005, 2006 Robert A. Beezer

#### Theorem PEEF Properties of Extended Echelon Form

160

Suppose that A is an  $m \times n$  matrix and that N is its extended echelon form. Then

- 1. J is nonsingular.
- 2. B = JA.
- 3. If  $\mathbf{x} \in \mathbb{C}^n$  and  $\mathbf{y} \in \mathbb{C}^m$ , then  $A\mathbf{x} = \mathbf{y}$  if and only if  $B\mathbf{x} = J\mathbf{y}$ .
- 4. C is in reduced row-echelon form, has no zero rows and has r pivot columns.
- 5. L is in reduced row-echelon form, has no zero rows and has m-r pivot columns.

Suppose A is an  $m \times n$  matrix with extended echelon form N. Suppose the reduced row-echelon form of A has r nonzero rows. Then C is the submatrix of N formed from the first r rows and the first n columns and L is the submatrix of N formed from the last m columns and the last m-r rows. Then

- 1. The null space of A is the null space of C,  $\mathcal{N}(A) = \mathcal{N}(C)$ .
- 2. The row space of A is the row space of C,  $\mathcal{R}(A) = \mathcal{R}(C)$ .
- 3. The column space of A is the null space of L,  $C(A) = \mathcal{N}(L)$ .
- 4. The left null space of A is the row space of L,  $\mathcal{L}(A) = \mathcal{R}(L)$ .

© 2005, 2006 Robert A. Beezer

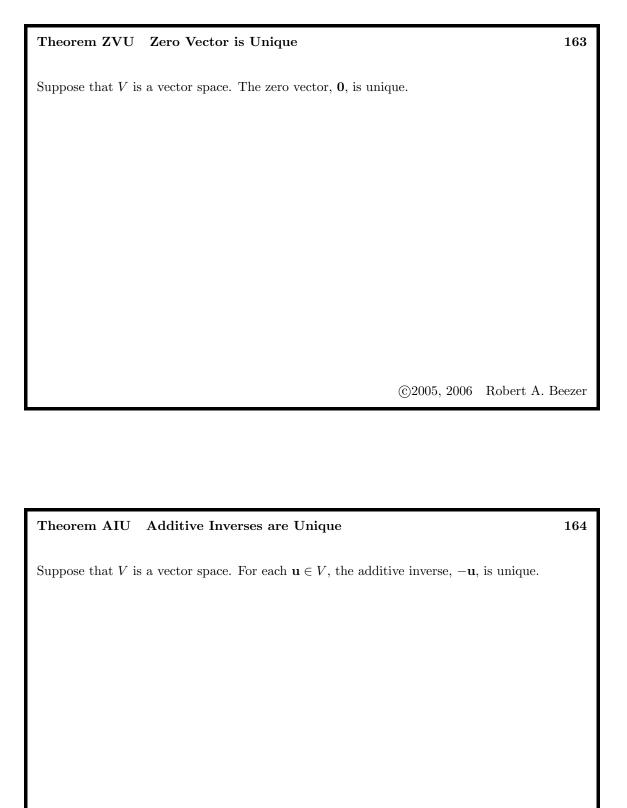
#### Definition VS Vector Space

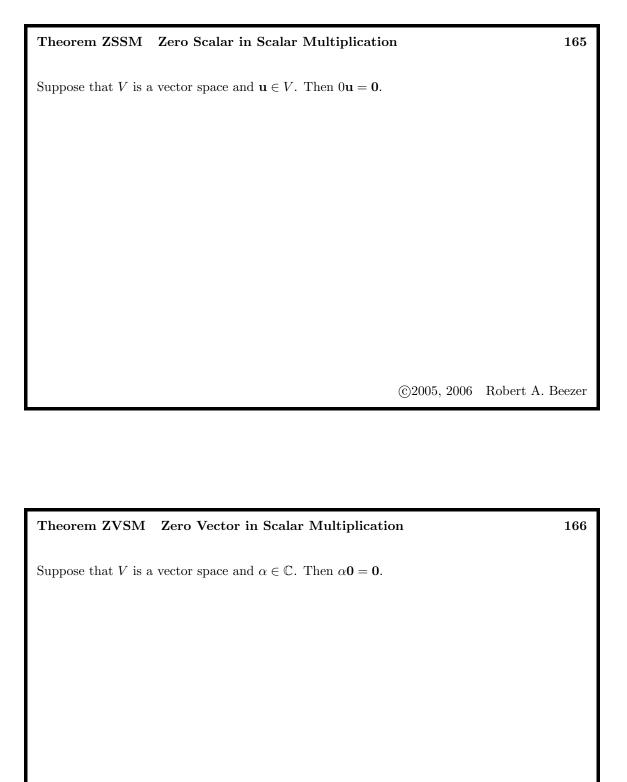
162

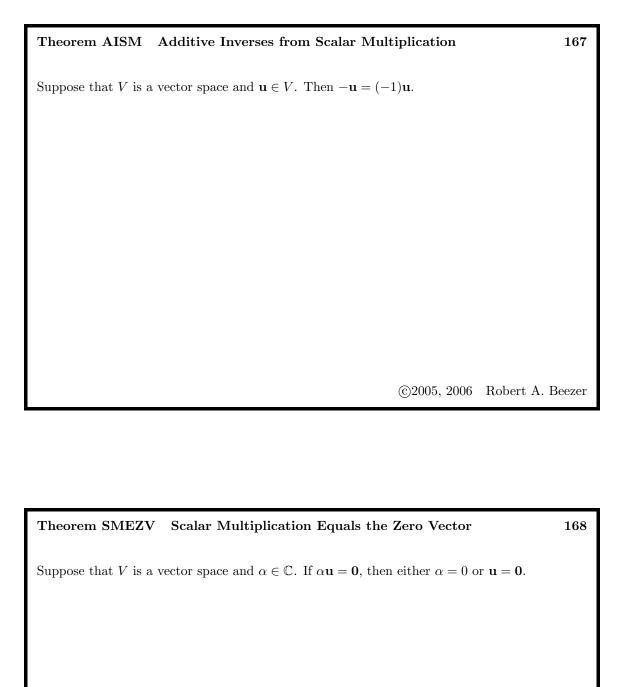
Suppose that V is a set upon which we have defined two operations: (1) **vector addition**, which combines two elements of V and is denoted by "+", and (2) **scalar multiplication**, which combines a complex number with an element of V and is denoted by juxtaposition. Then V, along with the two operations, is a **vector space** if the following ten properties hold.

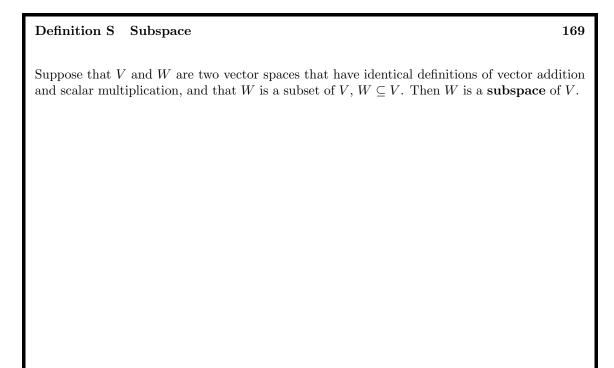
- AC Additive Closure If  $\mathbf{u}, \mathbf{v} \in V$ , then  $\mathbf{u} + \mathbf{v} \in V$ .
- SC Scalar Closure If  $\alpha \in \mathbb{C}$  and  $\mathbf{u} \in V$ , then  $\alpha \mathbf{u} \in V$ .
- C Commutativity If  $\mathbf{u}, \mathbf{v} \in V$ , then  $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$ .
- AA Additive Associativity If  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w} \in V$ , then  $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$ .
- **Z Zero Vector** There is a vector, **0**, called the **zero vector**, such that  $\mathbf{u} + \mathbf{0} = \mathbf{u}$  for all  $\mathbf{u} \in V$ .
- AI Additive Inverses If  $\mathbf{u} \in V$ , then there exists a vector  $-\mathbf{u} \in V$  so that  $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$ .
- SMA Scalar Multiplication Associativity If  $\alpha, \beta \in \mathbb{C}$  and  $\mathbf{u} \in V$ , then  $\alpha(\beta \mathbf{u}) = (\alpha \beta) \mathbf{u}$ .
- DVA Distributivity across Vector Addition If  $\alpha \in \mathbb{C}$  and  $\mathbf{u}, \mathbf{v} \in V$ , then  $\alpha(\mathbf{u} + \mathbf{v}) = \alpha \mathbf{u} + \alpha \mathbf{v}$ .
- DSA Distributivity across Scalar Addition If  $\alpha$ ,  $\beta \in \mathbb{C}$  and  $\mathbf{u} \in V$ , then  $(\alpha + \beta)\mathbf{u} = \alpha \mathbf{u} + \beta \mathbf{u}$ .
- $\bullet$  One If  $u \in V$ , then 1u = u

The objects in V are called **vectors**, no matter what else they might really be, simply by virtue of being elements of a vector space.









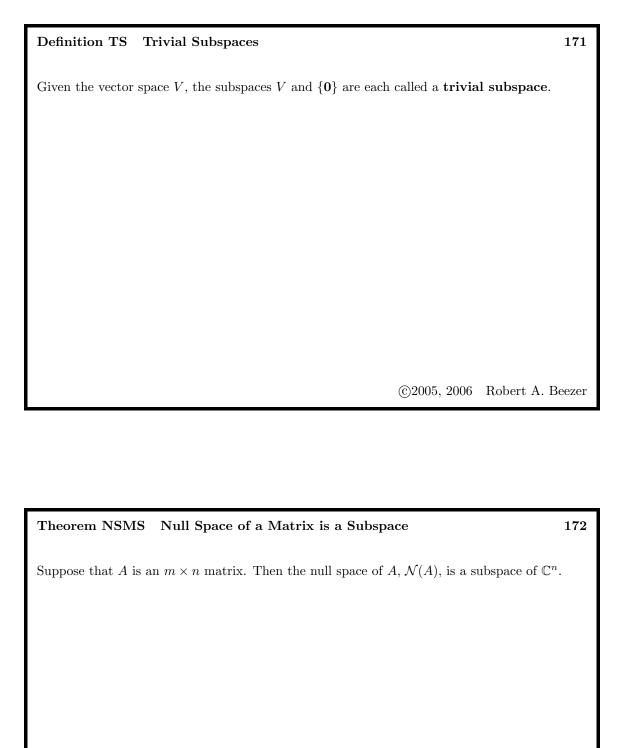
# Theorem TSS Testing Subsets for Subspaces

170

Suppose that V is a vector space and W is a subset of V,  $W \subseteq V$ . Endow W with the same operations as V. Then W is a subspace if and only if three conditions are met

- 1. W is non-empty,  $W \neq \emptyset$ .
- 2. If  $\mathbf{x} \in W$  and  $\mathbf{y} \in W$ , then  $\mathbf{x} + \mathbf{y} \in W$ .
- 3. If  $\alpha \in \mathbb{C}$  and  $\mathbf{x} \in W$ , then  $\alpha \mathbf{x} \in W$ .

© 2005, 2006 Robert A. Beezer



## Definition LC Linear Combination

173

Suppose that V is a vector space. Given n vectors  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_n$  and n scalars  $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n$ , their **linear combination** is the vector

$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \dots + \alpha_n \mathbf{u}_n.$$

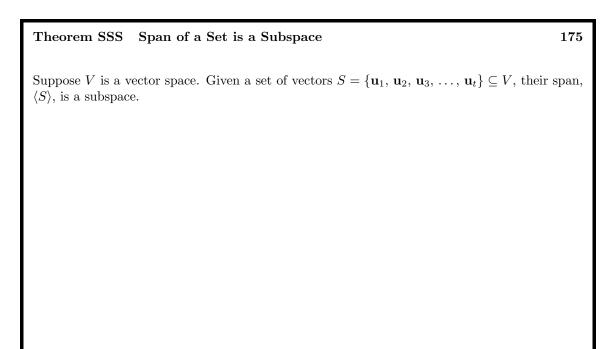
© 2005, 2006 Robert A. Beezer

#### Definition SS Span of a Set

174

Suppose that V is a vector space. Given a set of vectors  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$ , their **span**,  $\langle S \rangle$ , is the set of all possible linear combinations of  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t$ . Symbolically,

$$\langle S \rangle = \left\{ \alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \dots + \alpha_t \mathbf{u}_t \mid \alpha_i \in \mathbb{C}, \ 1 \le i \le t \right\}$$
$$= \left\{ \sum_{i=1}^t \alpha_i \mathbf{u}_i \mid \alpha_i \in \mathbb{C}, \ 1 \le i \le t \right\}$$



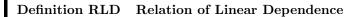
# Theorem CSMS Column Space of a Matrix is a Subspace

176

Suppose that A is an  $m \times n$  matrix. Then  $\mathcal{C}(A)$  is a subspace of  $\mathbb{C}^m$ .

©2005, 2006 Robert A. Beezer

	177		
Suppose that A is an $m \times n$ matrix. Then $\mathcal{R}(A)$ is a subspace of $\mathbb{C}^n$ .			
©2005, 2006	Robert A. Beezer		
Theorem LNSMS Left Null Space of a Matrix is a Subspace	178		
Theorem LNSMS Left Null Space of a Matrix is a Subspace Suppose that $A$ is an $m \times n$ matrix. Then $\mathcal{L}(A)$ is a subspace of $\mathbb{C}^m$ .	178		
	178		
	178		



Suppose that V is a vector space. Given a set of vectors  $S = \{\mathbf{u}_1, \, \mathbf{u}_2, \, \mathbf{u}_3, \, \dots, \, \mathbf{u}_n\}$ , an equation of the form

$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \dots + \alpha_n \mathbf{u}_n = \mathbf{0}$$

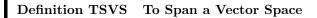
is a **relation of linear dependence** on S. If this equation is formed in a trivial fashion, i.e.  $\alpha_i = 0, 1 \le i \le n$ , then we say it is a **trivial relation of linear dependence** on S.

© 2005, 2006 Robert A. Beezer

# Definition LI Linear Independence

180

Suppose that V is a vector space. The set of vectors  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  from V is linearly dependent if there is a relation of linear dependence on S that is not trivial. In the case where the *only* relation of linear dependence on S is the trivial one, then S is a **linearly independent** set of vectors.



Suppose V is a vector space. A subset S of V is a **spanning set** for V if  $\langle S \rangle = V$ . In this case, we also say S **spans** V.

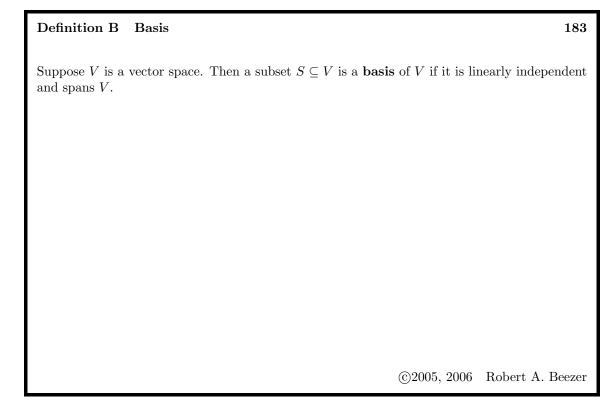
©2005, 2006 Robert A. Beezer

# Theorem VRRB Vector Representation Relative to a Basis

182

Suppose that V is a vector space and  $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_m\}$  is a linearly independent set that spans V. Let  $\mathbf{w}$  be any vector in V. Then there exist *unique* scalars  $a_1, a_2, a_3, \dots, a_m$  such that

$$\mathbf{w} = a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2 + a_3 \mathbf{v}_3 + \dots + a_m \mathbf{v}_m.$$



#### Theorem SUVB Standard Unit Vectors are a Basis

184

The set of standard unit vectors for  $\mathbb{C}^m$  (Definition SUV),  $B = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \dots, \mathbf{e}_m\} = \{\mathbf{e}_i \mid 1 \leq i \leq m\}$  is a basis for the vector space  $\mathbb{C}^m$ .



Suppose that A is a square matrix of size m. Then the columns of A are a basis of  $\mathbb{C}^m$  if and only if A is nonsingular.

© 2005, 2006 Robert A. Beezer

## Theorem NME5 Nonsingular Matrix Equivalences, Round 5

186

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- $2.\ A$  row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .
- 8. The columns of A are a basis for  $\mathbb{C}^n$ .



188

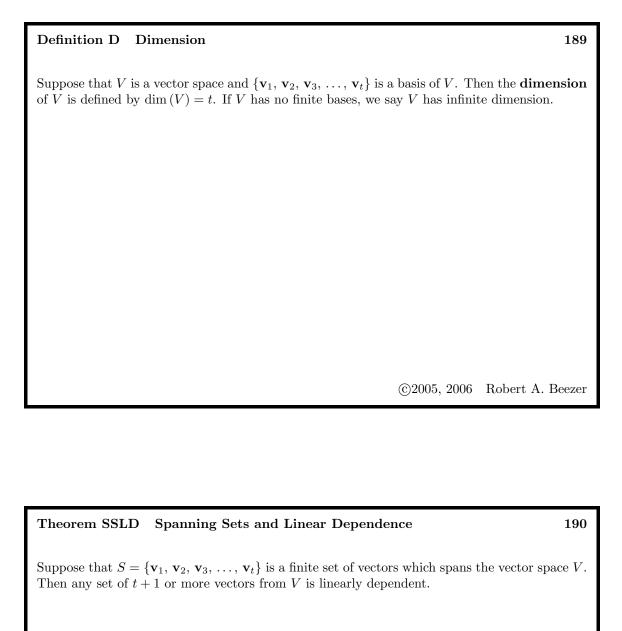
Suppose that  $B = \{\mathbf{v}_1, \, \mathbf{v}_2, \, \mathbf{v}_3, \, \dots, \, \mathbf{v}_p\}$  is an orthonormal basis of the subspace W of  $\mathbb{C}^m$ . For any  $\mathbf{w} \in W$ ,

$$\mathbf{w} = \langle \mathbf{w}, \, \mathbf{v}_1 \rangle \, \mathbf{v}_1 + \langle \mathbf{w}, \, \mathbf{v}_2 \rangle \, \mathbf{v}_2 + \langle \mathbf{w}, \, \mathbf{v}_3 \rangle \, \mathbf{v}_3 + \dots + \langle \mathbf{w}, \, \mathbf{v}_p \rangle \, \mathbf{v}_p$$

© 2005, 2006 Robert A. Beezer

# 

Suppose that U is a unitary matrix of sixe n and  $B = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_n\}$  is an orthonormal basis of  $\mathbb{C}^n$ . Then the set  $C = \{U\mathbf{x}_1, U\mathbf{x}_2, U\mathbf{x}_3, \dots, U\mathbf{x}_n\}$  is an orthonormal basis of  $\mathbb{C}^n$ .



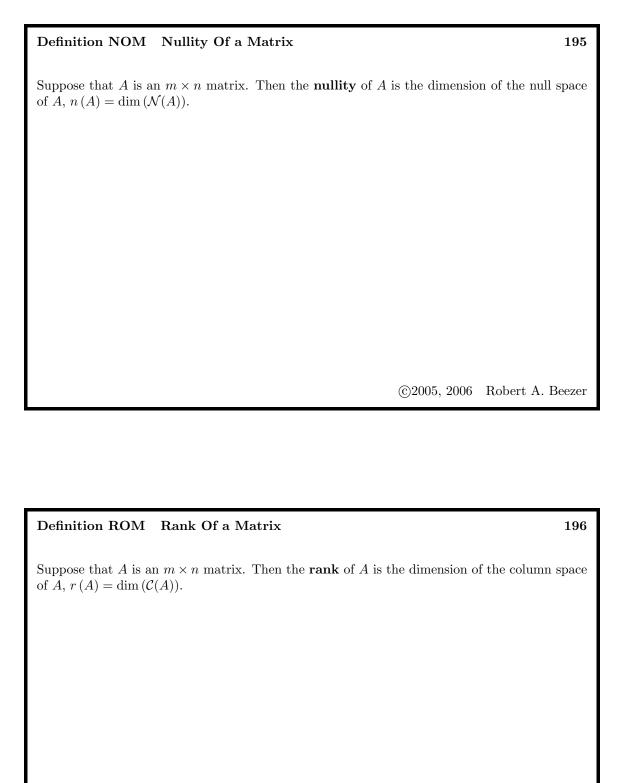
Theorem DIS Dases have identical Sizes	191
Suppose that $V$ is a vector space with a finite basis $B$ and a second basis $C$ .	Then $B$ and $C$
have the same size.	
©2005, 2006 F	Robert A. Beezer
Theorem DCM Dimension of $\mathbb{C}^m$	192
The dimension of $\mathbb{C}^m$ (Example VSCV) is $m$ .	

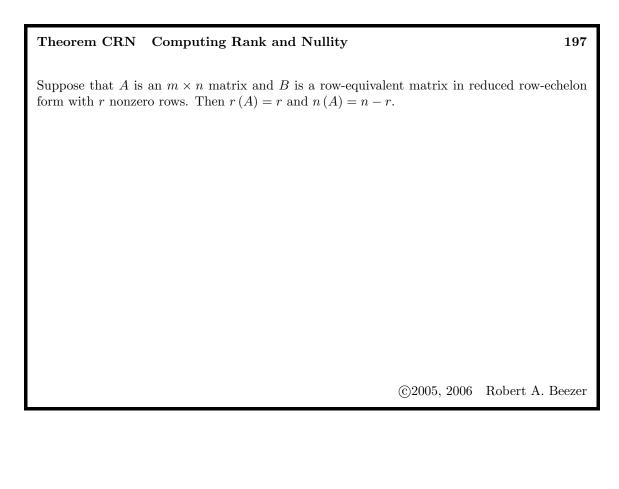
Theorem DP D	Dimension of $P_n$		193
The dimension of $I$	$P_n$ (Example VSP) is $n+1$ .		
		©2005, 2006	Robert A. Beezer

# Theorem DM Dimension of $M_{mn}$

 $\bf 194$ 

The dimension of  $M_{mn}$  (Example VSM) is mn.





# Theorem RPNC Rank Plus Nullity is Columns

198

Suppose that A is an  $m \times n$  matrix. Then r(A) + n(A) = n.

## Theorem RNNM Rank and Nullity of a Nonsingular Matrix

199

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. The rank of A is n, r(A) = n.
- 3. The nullity of A is zero, n(A) = 0.

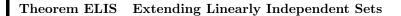
© 2005, 2006 Robert A. Beezer

#### Theorem NME6 Nonsingular Matrix Equivalences, Round 6

200

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .
- 8. The columns of A are a basis for  $\mathbb{C}^n$ .
- 9. The rank of A is n, r(A) = n.
- 10. The nullity of A is zero, n(A) = 0.



Suppose V is vector space and S is a linearly independent set of vectors from V. Suppose  $\mathbf{w}$  is a vector such that  $\mathbf{w} \notin \langle S \rangle$ . Then the set  $S' = S \cup \{\mathbf{w}\}$  is linearly independent.

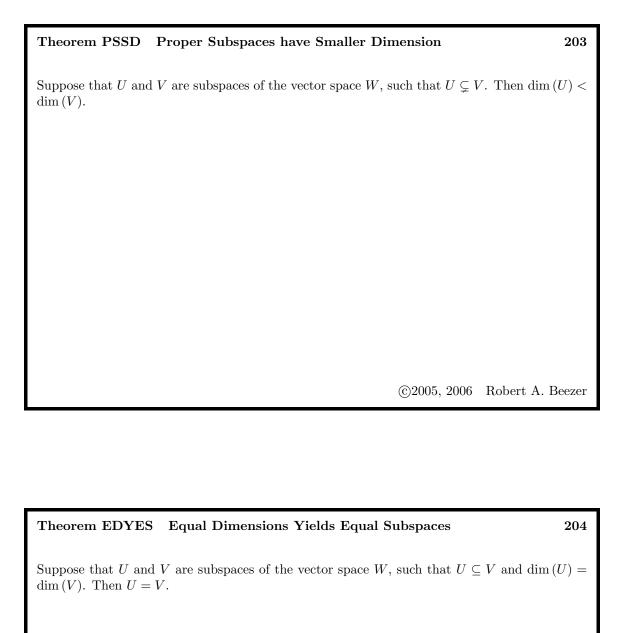
© 2005, 2006 Robert A. Beezer

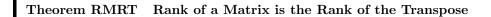
#### Theorem G Goldilocks

202

Suppose that V is a vector space of dimension t. Let  $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_m\}$  be a set of vectors from V. Then

- 1. If m > t, then S is linearly dependent.
- 2. If m < t, then S does not span V.
- 3. If m = t and S is linearly independent, then S spans V.
- 4. If m = t and S spans V, then S is linearly independent.





Suppose A is an  $m \times n$  matrix. Then  $r(A) = r(A^t)$ .

©2005, 2006 Robert A. Beezer

# Theorem DFS Dimensions of Four Subspaces

206

Suppose that A is an  $m \times n$  matrix, and B is a row-equivalent matrix in reduced row-echelon form with r nonzero rows. Then

- 1. dim  $(\mathcal{N}(A)) = n r$
- 2. dim  $(\mathcal{C}(A)) = r$
- 3. dim  $(\mathcal{R}(A)) = r$
- 4. dim  $(\mathcal{L}(A)) = m r$

#### Definition DS Direct Sum

207

Suppose that V is a vector space with two subspaces U and W such that for every  $\mathbf{v} \in V$ ,

- 1. There exists vectors  $\mathbf{u} \in U$ ,  $\mathbf{w} \in W$  such that  $\mathbf{v} = \mathbf{u} + \mathbf{w}$
- 2. If  $\mathbf{v} = \mathbf{u}_1 + \mathbf{w}_1$  and  $\mathbf{v} = \mathbf{u}_2 + \mathbf{w}_2$  where  $\mathbf{u}_1, \mathbf{u}_2 \in U, \mathbf{w}_1, \mathbf{w}_2 \in W$  then  $\mathbf{u}_1 = \mathbf{u}_2$  and  $\mathbf{w}_1 = \mathbf{w}_2$ .

Then V is the **direct sum** of U and W and we write  $V = U \oplus W$ .

© 2005, 2006 Robert A. Beezer

#### Theorem DSFB Direct Sum From a Basis

208

Suppose that V is a vector space with a basis  $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$ . Define

$$U = \langle \{\mathbf{v}_1, \, \mathbf{v}_2, \, \mathbf{v}_3, \, \dots, \, \mathbf{v}_m \} \rangle \qquad W = \langle \{\mathbf{v}_{m+1}, \, \mathbf{v}_{m+2}, \, \mathbf{v}_{m+3}, \, \dots, \, \mathbf{v}_n \} \rangle$$

Then  $V = U \oplus W$ .



Suppose that U is a subspace of the vector space V. Then there exists a subspace W of V such that  $V = U \oplus W$ .

©2005, 2006 Robert A. Beezer

#### Theorem DSZV Direct Sums and Zero Vectors

210

Suppose U and W are subspaces of the vector space V. Then  $V = U \oplus W$  if and only if

- 1. For every  $\mathbf{v} \in V$ , there exists vectors  $\mathbf{u} \in U$ ,  $\mathbf{w} \in W$  such that  $\mathbf{v} = \mathbf{u} + \mathbf{w}$ .
- 2. Whenever  $\mathbf{0} = \mathbf{u} + \mathbf{w}$  with  $\mathbf{u} \in U$ ,  $\mathbf{w} \in W$  then  $\mathbf{u} = \mathbf{w} = \mathbf{0}$ .

#### Theorem DSZI Direct Sums and Zero Intersection

211

Suppose U and W are subspaces of the vector space V. Then  $V=U\oplus W$  if and only if

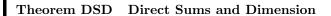
- 1. For every  $\mathbf{v} \in V$ , there exists vectors  $\mathbf{u} \in U$ ,  $\mathbf{w} \in W$  such that  $\mathbf{v} = \mathbf{u} + \mathbf{w}$ .
- 2.  $U \cap W = \{0\}.$

©2005, 2006 Robert A. Beezer

#### Theorem DSLI Direct Sums and Linear Independence

212

Suppose U and W are subspaces of the vector space V with  $V = U \oplus W$ . Suppose that R is a linearly independent subset of U and S is a linearly independent subset of W. Then  $R \cup S$  is a linearly independent subset of V.



Suppose U and W are subspaces of the vector space V with  $V = U \oplus W$ . Then  $\dim(V) = \dim(U) + \dim(W)$ .

©2005, 2006 Robert A. Beezer

# Theorem RDS Repeated Direct Sums

214

Suppose V is a vector space with subspaces U and W with  $V=U\oplus W$ . Suppose that X and Y are subspaces of W with  $W=X\oplus Y$ . Then  $V=U\oplus X\oplus Y$ .

1.  $E_{i,j}$  is the square matrix of size n with

$$[E_{i,j}]_{k\ell} = \begin{cases} 0 & k \neq i, k \neq j, \ell \neq k \\ 1 & k \neq i, k \neq j, \ell = k \\ 0 & k = i, \ell \neq j \\ 1 & k = i, \ell = j \\ 0 & k = j, \ell \neq i \\ 1 & k = j, \ell = i \end{cases}$$

2.  $E_i(\alpha)$ , for  $\alpha \neq 0$ , is the square matrix of size n with

$$[E_i(\alpha)]_{k\ell} = \begin{cases} 0 & k \neq i, \ell \neq k \\ 1 & k \neq i, \ell = k \\ \alpha & k = i, \ell = i \end{cases}$$

3.  $E_{i,j}(\alpha)$  is the square matrix of size n with

$$[E_{i,j}(\alpha)]_{k\ell} = \begin{cases} 0 & k \neq j, \ell \neq k \\ 1 & k \neq j, \ell = k \\ 0 & k = j, \ell \neq i, \ell \neq j \\ 1 & k = j, \ell = j \end{cases}$$

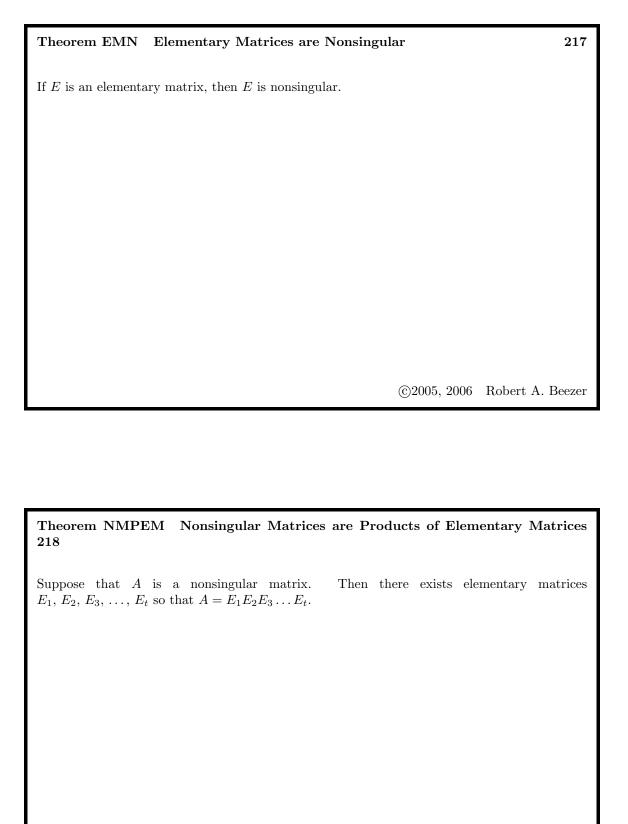
©2005, 2006 Robert A. Beezer

## Theorem EMDRO Elementary Matrices Do Row Operations

216

Suppose that A is a matrix, and B is a matrix of the same size that is obtained from A by a single row operation (Definition RO).

- 1. If the row operation swaps rows i and j, then  $B = E_{i,j}A$ .
- 2. If the row operation multiplies row i by  $\alpha$ , then  $B = E_i(\alpha) A$ .
- 3. If the row operation multiplies row i by  $\alpha$  and adds the result to row j, then  $B = E_{i,j}(\alpha) A$ .





Suppose that A is an  $m \times n$  matrix. Then the **submatrix** A(i|j) is the  $(m-1) \times (n-1)$  matrix obtained from A by removing row i and column j.

© 2005, 2006 Robert A. Beezer

#### Definition DM Determinant of a Matrix

220

Suppose A is a square matrix. Then its **determinant**,  $\det(A) = |A|$ , is an element of  $\mathbb{C}$  defined recursively by:

If A is a  $1 \times 1$  matrix, then  $\det(A) = [A]_{11}$ .

If A is a matrix of size n with  $n \geq 2$ , then

$$\begin{split} \det{(A)} &= [A]_{11} \det{(A\,(1|1))} - [A]_{12} \det{(A\,(1|2))} + [A]_{13} \det{(A\,(1|3))} - \\ & [A]_{14} \det{(A\,(1|4))} + \dots + (-1)^{n+1} \, [A]_{1n} \det{(A\,(1|n))} \end{split}$$

Theorem DMST	Determinant	of Matricos	of Sizo	Two
i neorem Divis i	Determinant	or matrices	or Size	$1\mathbf{wo}$

Suppose that  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ . Then  $\det{(A)} = ad - bc$ 

© 2005, 2006 Robert A. Beezer

# Theorem DER Determinant Expansion about Rows

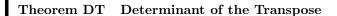
222

**221** 

Suppose that A is a square matrix of size n. Then

$$\det(A) = (-1)^{i+1} [A]_{i1} \det(A(i|1)) + (-1)^{i+2} [A]_{i2} \det(A(i|2))$$
$$+ (-1)^{i+3} [A]_{i3} \det(A(i|3)) + \dots + (-1)^{i+n} [A]_{in} \det(A(i|n)) \qquad 1 \le i \le n$$

which is known as **expansion** about row i.



Suppose that A is a square matrix. Then  $\det(A^t) = \det(A)$ .

©2005, 2006 Robert A. Beezer

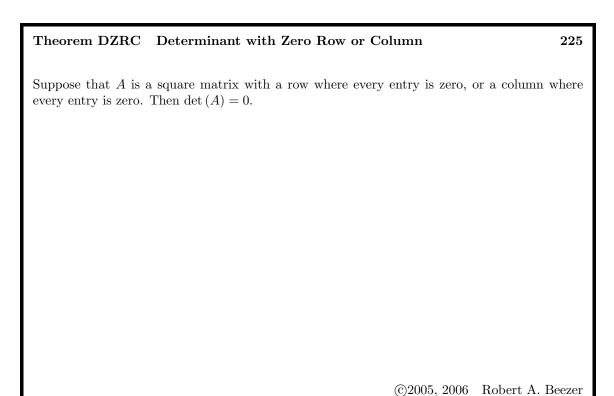
# Theorem DEC Determinant Expansion about Columns

224

Suppose that A is a square matrix of size n. Then

$$\begin{split} \det{(A)} &= (-1)^{1+j} \left[ A \right]_{1j} \det{(A \, (1|j))} + (-1)^{2+j} \left[ A \right]_{2j} \det{(A \, (2|j))} \\ &+ (-1)^{3+j} \left[ A \right]_{3j} \det{(A \, (3|j))} + \dots + (-1)^{n+j} \left[ A \right]_{nj} \det{(A \, (n|j))} \qquad 1 \leq j \leq n \end{split}$$

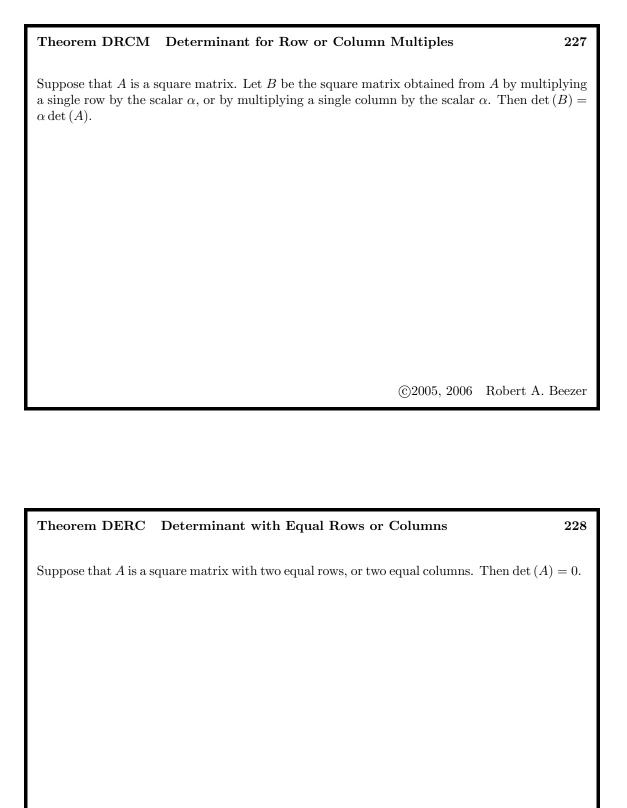
which is known as **expansion** about column j.

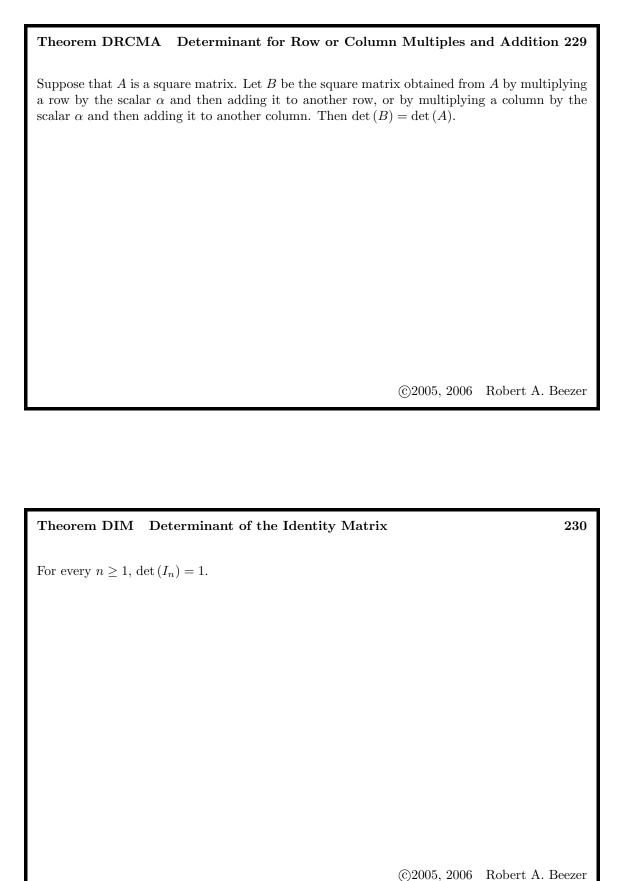


## Theorem DRCS Determinant for Row or Column Swap

226

Suppose that A is a square matrix. Let B be the square matrix obtained from A by interchanging the location of two rows, or interchanging the location of two columns. Then  $\det(B) = -\det(A)$ .





For the three possible versions of an elementary matrix (Definition ELEM) we have the determinants,

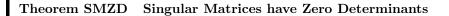
- 1.  $\det(E_{i,j}) = -1$
- 2.  $\det (E_i(\alpha)) = \alpha$
- 3.  $\det (E_{i,j}(\alpha)) = 1$

©2005, 2006 Robert A. Beezer

# Theorem DEMMM Determinants, Elementary Matrices, Matrix Multiplication 232

Suppose that A is a square matrix of size n and E is any elementary matrix of size n. Then

$$\det(EA) = \det(E)\det(A)$$



234

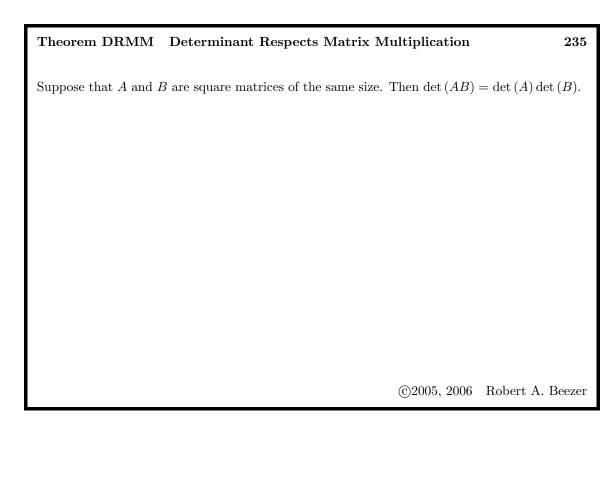
Let A be a square matrix. Then A is singular if and only if det(A) = 0.

© 2005, 2006 Robert A. Beezer

# Theorem NME7 Nonsingular Matrix Equivalences, Round 7

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .
- 8. The columns of A are a basis for  $\mathbb{C}^n$ .
- 9. The rank of A is n, r(A) = n.
- 10. The nullity of A is zero, n(A) = 0.
- 11. The determinant of A is nonzero,  $det(A) \neq 0$ .

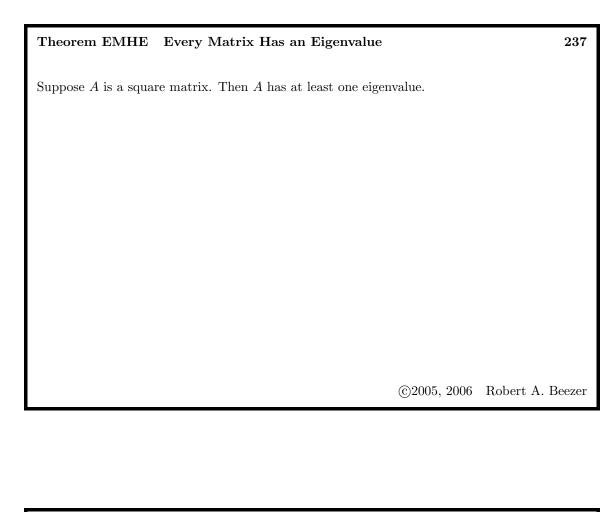


# Definition EEM Eigenvalues and Eigenvectors of a Matrix

**236** 

Suppose that A is a square matrix of size n,  $\mathbf{x} \neq \mathbf{0}$  is a vector in  $\mathbb{C}^n$ , and  $\lambda$  is a scalar in  $\mathbb{C}$ . Then we say  $\mathbf{x}$  is an **eigenvector** of A with **eigenvalue**  $\lambda$  if

$$A\mathbf{x} = \lambda \mathbf{x}$$

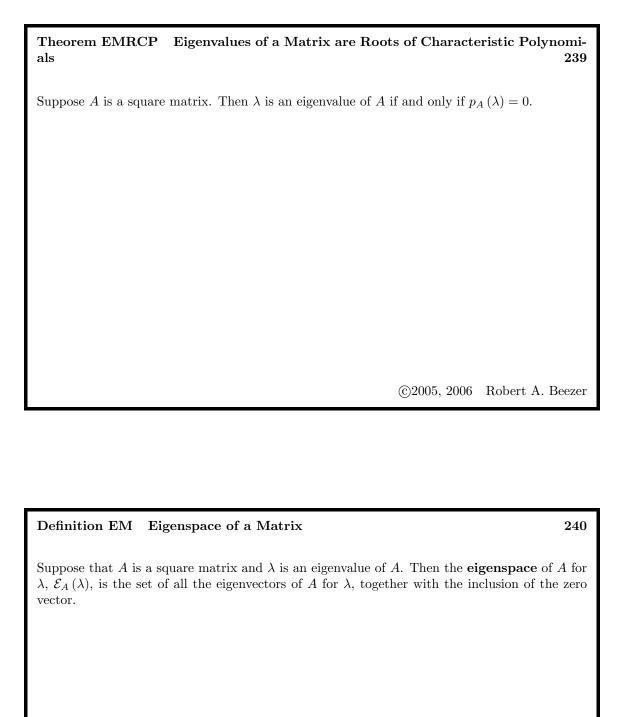


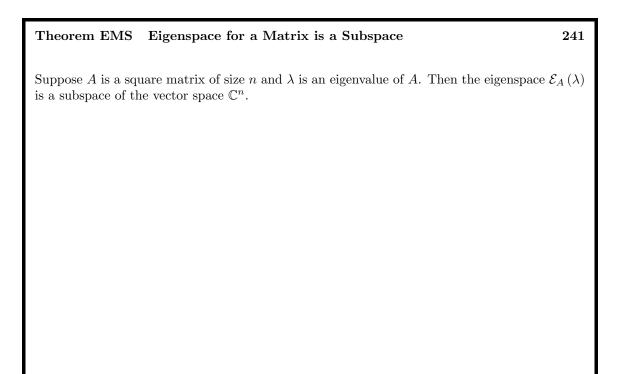
# Definition CP Characteristic Polynomial

238

Suppose that A is a square matrix of size n. Then the **characteristic polynomial** of A is the polynomial  $p_{A}(x)$  defined by

$$p_A(x) = \det(A - xI_n)$$





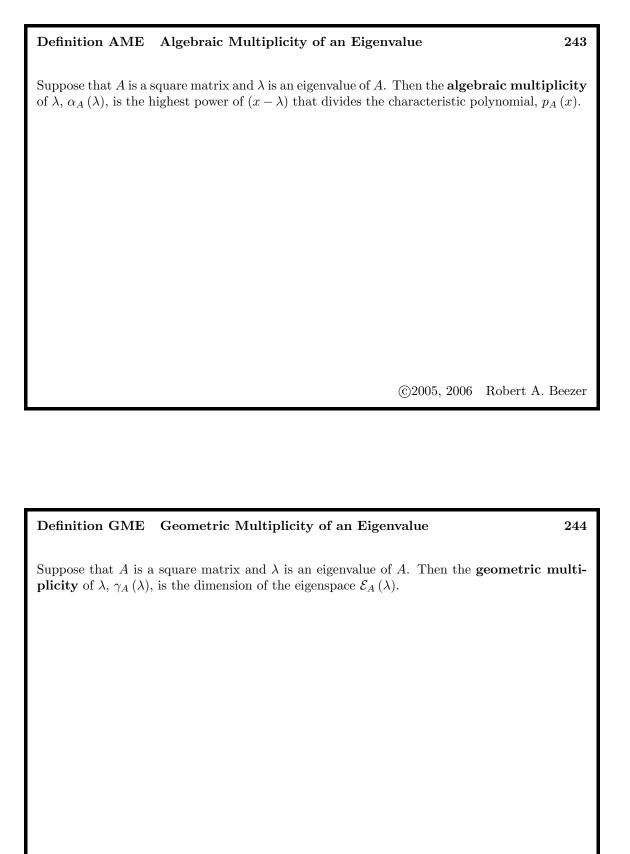
# Theorem EMNS Eigenspace of a Matrix is a Null Space

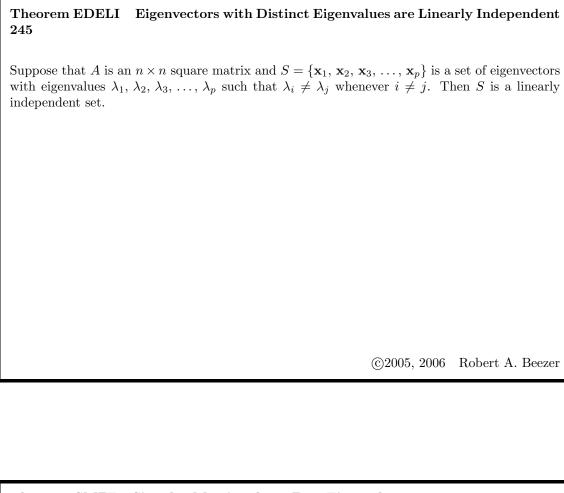
242

Suppose A is a square matrix of size n and  $\lambda$  is an eigenvalue of A. Then

$$\mathcal{E}_A(\lambda) = \mathcal{N}(A - \lambda I_n)$$

©2005, 2006 Robert A. Beezer





# Theorem SMZE Singular Matrices have Zero Eigenvalues

246

Suppose A is a square matrix. Then A is singular if and only if  $\lambda = 0$  is an eigenvalue of A.

## Theorem NME8 Nonsingular Matrix Equivalences, Round 8

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .
- 8. The columns of A are a basis for  $\mathbb{C}^n$ .
- 9. The rank of A is n, r(A) = n.
- 10. The nullity of A is zero, n(A) = 0.
- 11. The determinant of A is nonzero,  $\det(A) \neq 0$ .
- 12.  $\lambda = 0$  is not an eigenvalue of A.

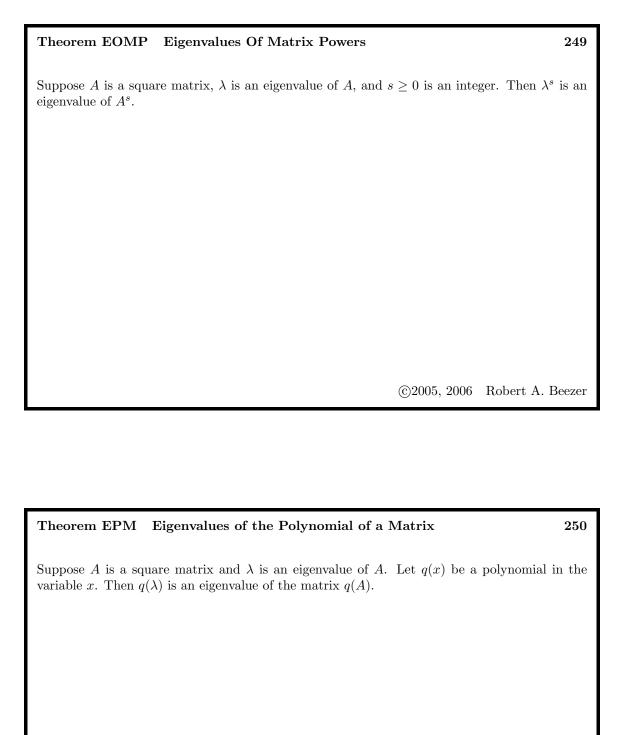
©2005, 2006 Robert A. Beezer

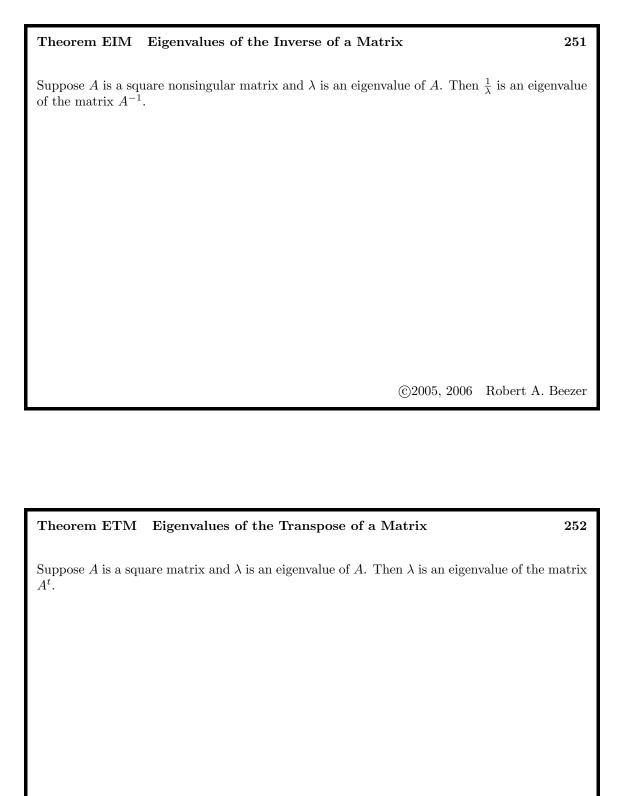
# Theorem ESMM Eigenvalues of a Scalar Multiple of a Matrix

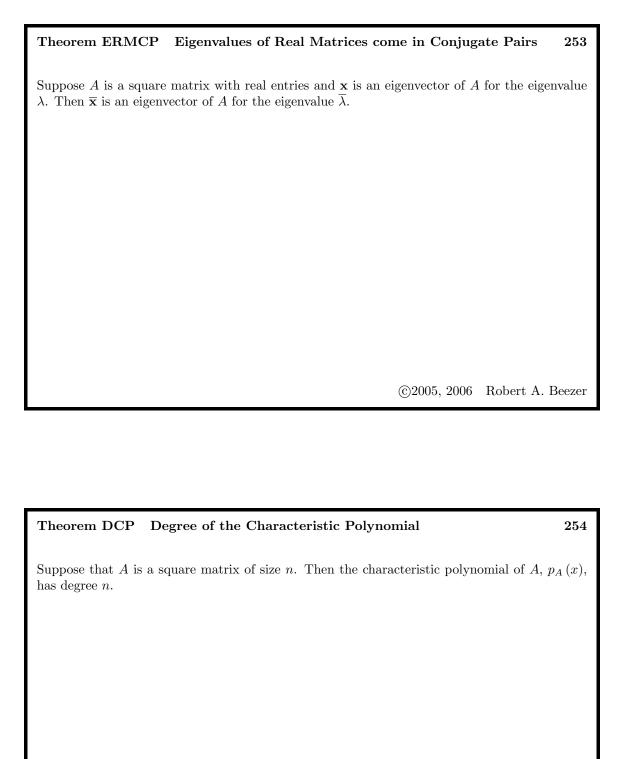
248

247

Suppose A is a square matrix and  $\lambda$  is an eigenvalue of A. Then  $\alpha\lambda$  is an eigenvalue of  $\alpha A$ .







# Theorem NEM Number of Eigenvalues of a Matrix

**255** 

Suppose that A is a square matrix of size n with distinct eigenvalues  $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k$ . Then

$$\sum_{i=1}^{k} \alpha_A \left( \lambda_i \right) = n$$

©2005, 2006 Robert A. Beezer

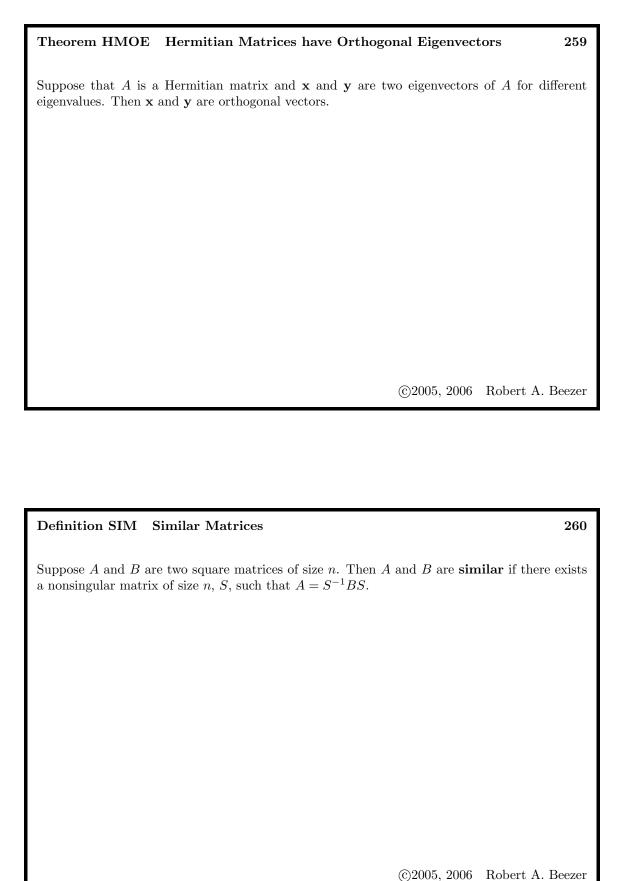
# Theorem ME Multiplicities of an Eigenvalue

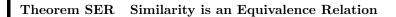
256

Suppose that A is a square matrix of size n and  $\lambda$  is an eigenvalue. Then

$$1 \le \gamma_A(\lambda) \le \alpha_A(\lambda) \le n$$

Theorem MNEM Maximum Number of Eigenvalues of a Matrix	257
Suppose that $A$ is a square matrix of size $n$ . Then $A$ cannot have more than $n$ or $n$ to $n$ or $n$ to $n$ or $n$ or $n$ to $n$ or $n$ o	distinct eigen-
values.	
©2005, 2006 Rob	pert A. Beezer
Theorem HMRE Hermitian Matrices have Real Eigenvalues	258
Theorem HMRE Hermitian Matrices have Real Eigenvalues $ \text{Suppose that } A \text{ is a Hermitian matrix and } \lambda \text{ is an eigenvalue of } A. \text{ Then } \lambda \in \mathbb{R}. $	258
	258
	258
	258
	258
	258
	258
	258





Suppose A, B and C are square matrices of size n. Then

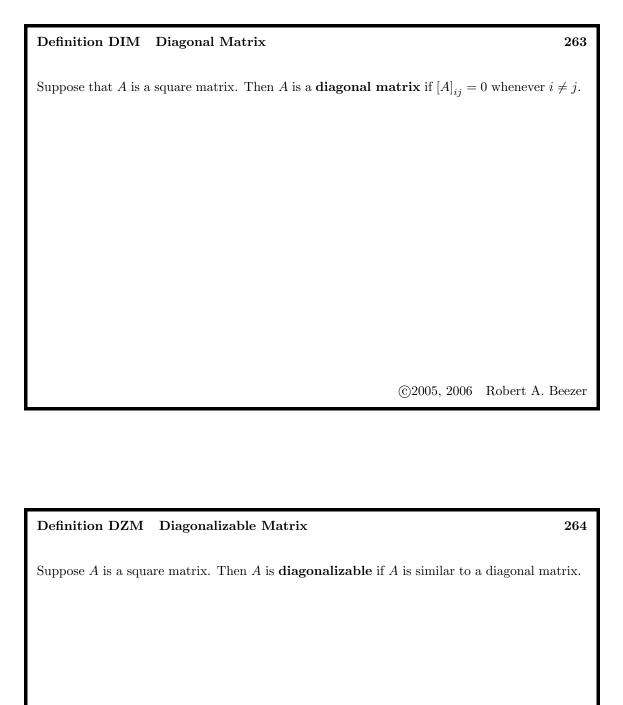
- 1. A is similar to A. (Reflexive)
- 2. If A is similar to B, then B is similar to A. (Symmetric)
- 3. If A is similar to B and B is similar to C, then A is similar to C. (Transitive)

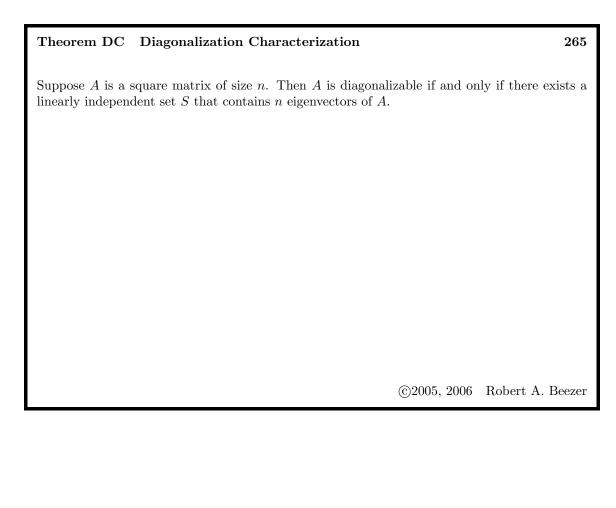
©2005, 2006 Robert A. Beezer

# Theorem SMEE Similar Matrices have Equal Eigenvalues

262

Suppose A and B are similar matrices. Then the characteristic polynomials of A and B are equal, that is  $p_A(x) = p_B(x)$ .

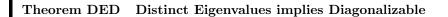




# Theorem DMFE Diagonalizable Matrices have Full Eigenspaces

**266** 

Suppose A is a square matrix. Then A is diagonalizable if and only if  $\gamma_A(\lambda) = \alpha_A(\lambda)$  for every eigenvalue  $\lambda$  of A.



Suppose A is a square matrix of size n with n distinct eigenvalues. Then A is diagonalizable.

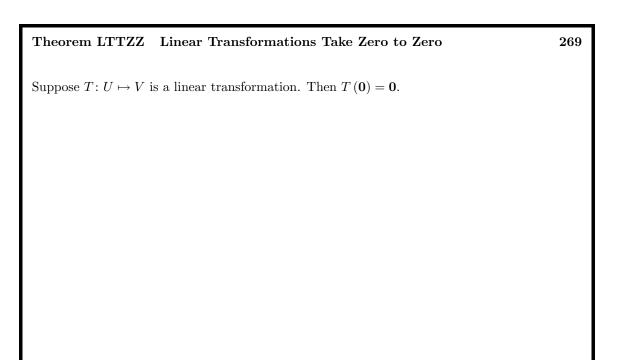
©2005, 2006 Robert A. Beezer

#### Definition LT Linear Transformation

**268** 

A linear transformation,  $T \colon U \mapsto V$ , is a function that carries elements of the vector space U (called the **domain**) to the vector space V (called the **codomain**), and which has two additional properties

- 1.  $T(\mathbf{u}_1 + \mathbf{u}_2) = T(\mathbf{u}_1) + T(\mathbf{u}_2)$  for all  $\mathbf{u}_1, \mathbf{u}_2 \in U$
- 2.  $T(\alpha \mathbf{u}) = \alpha T(\mathbf{u})$  for all  $\mathbf{u} \in U$  and all  $\alpha \in \mathbb{C}$

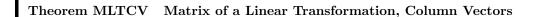


Theorem MBLT Matrices Build Linear Transformations

270

Suppose that A is an  $m \times n$  matrix. Define a function  $T: \mathbb{C}^n \mapsto \mathbb{C}^m$  by  $T(\mathbf{x}) = A\mathbf{x}$ . Then T is a linear transformation.

©2005, 2006 Robert A. Beezer



Suppose that  $T: \mathbb{C}^n \to \mathbb{C}^m$  is a linear transformation. Then there is an  $m \times n$  matrix A such that  $T(\mathbf{x}) = A\mathbf{x}$ .

©2005, 2006 Robert A. Beezer

#### Theorem LTLC Linear Transformations and Linear Combinations

272

271

Suppose that  $T: U \mapsto V$  is a linear transformation,  $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_t$  are vectors from U and  $a_1, a_2, a_3, \ldots, a_t$  are scalars from  $\mathbb{C}$ . Then

$$T(a_1\mathbf{u}_1 + a_2\mathbf{u}_2 + a_3\mathbf{u}_3 + \dots + a_t\mathbf{u}_t) = a_1T(\mathbf{u}_1) + a_2T(\mathbf{u}_2) + a_3T(\mathbf{u}_3) + \dots + a_tT(\mathbf{u}_t)$$

#### Theorem LTDB Linear Transformation Defined on a Basis

273

Suppose that  $T: U \mapsto V$  is a linear transformation,  $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is a basis for U and  $\mathbf{w}$  is a vector from U. Let  $a_1, a_2, a_3, \dots, a_n$  be the scalars from  $\mathbb C$  such that

$$\mathbf{w} = a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2 + a_3 \mathbf{u}_3 + \dots + a_n \mathbf{u}_n$$

Then

$$T(\mathbf{w}) = a_1 T(\mathbf{u}_1) + a_2 T(\mathbf{u}_2) + a_3 T(\mathbf{u}_3) + \dots + a_n T(\mathbf{u}_n)$$

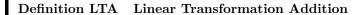
© 2005, 2006 Robert A. Beezer

#### Definition PI Pre-Image

274

Suppose that  $T: U \mapsto V$  is a linear transformation. For each  $\mathbf{v}$ , define the **pre-image** of  $\mathbf{v}$  to be the subset of U given by

$$T^{-1}(\mathbf{v}) = \{ \mathbf{u} \in U \mid T(\mathbf{u}) = \mathbf{v} \}$$



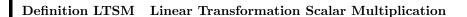
Suppose that  $T: U \mapsto V$  and  $S: U \mapsto V$  are two linear transformations with the same domain and codomain. Then their **sum** is the function  $T+S: U \mapsto V$  whose outputs are defined by

$$(T+S)(\mathbf{u}) = T(\mathbf{u}) + S(\mathbf{u})$$

© 2005, 2006 Robert A. Beezer

#### Theorem SLTLT Sum of Linear Transformations is a Linear Transformation 276

Suppose that  $T\colon U\mapsto V$  and  $S\colon U\mapsto V$  are two linear transformations with the same domain and codomain. Then  $T+S\colon U\mapsto V$  is a linear transformation.



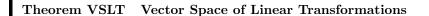
Suppose that  $T: U \mapsto V$  is a linear transformation and  $\alpha \in \mathbb{C}$ . Then the **scalar multiple** is the function  $\alpha T: U \mapsto V$  whose outputs are defined by

$$(\alpha T)(\mathbf{u}) = \alpha T(\mathbf{u})$$

©2005, 2006 Robert A. Beezer

# Theorem MLTLT Multiple of a Linear Transformation is a Linear Transformation 278

Suppose that  $T: U \mapsto V$  is a linear transformation and  $\alpha \in \mathbb{C}$ . Then  $(\alpha T): U \mapsto V$  is a linear transformation.



Suppose that U and V are vector spaces. Then the set of all linear transformations from U to V, LT (U, V) is a vector space when the operations are those given in Definition LTA and Definition LTSM.

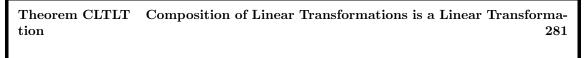
©2005, 2006 Robert A. Beezer

# Definition LTC Linear Transformation Composition

280

Suppose that  $T \colon U \mapsto V$  and  $S \colon V \mapsto W$  are linear transformations. Then the **composition** of S and T is the function  $(S \circ T) \colon U \mapsto W$  whose outputs are defined by

$$(S \circ T)(\mathbf{u}) = S(T(\mathbf{u}))$$



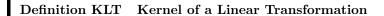
Suppose that  $T\colon U\mapsto V$  and  $S\colon V\mapsto W$  are linear transformations. Then  $(S\circ T)\colon U\mapsto W$  is a linear transformation.

©2005, 2006 Robert A. Beezer

# Definition ILT Injective Linear Transformation

282

Suppose  $T: U \mapsto V$  is a linear transformation. Then T is **injective** if whenever  $T(\mathbf{x}) = T(\mathbf{y})$ , then  $\mathbf{x} = \mathbf{y}$ .



Suppose  $T \colon U \mapsto V$  is a linear transformation. Then the **kernel** of T is the set

$$\mathcal{K}(T) = \{ \mathbf{u} \in U \mid T(\mathbf{u}) = \mathbf{0} \}$$

©2005, 2006 Robert A. Beezer

# Theorem KLTS Kernel of a Linear Transformation is a Subspace

284

Suppose that  $T:U\mapsto V$  is a linear transformation. Then the kernel of  $T,\,\mathcal{K}(T),$  is a subspace of U.

# Theorem KPI Kernel and Pre-Image

285

Suppose  $T: U \mapsto V$  is a linear transformation and  $\mathbf{v} \in V$ . If the preimage  $T^{-1}(\mathbf{v})$  is non-empty, and  $\mathbf{u} \in T^{-1}(\mathbf{v})$  then

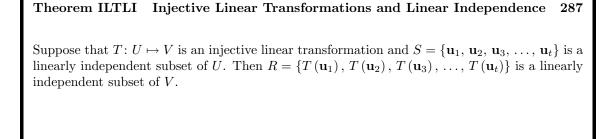
$$T^{-1}(\mathbf{v}) = {\mathbf{u} + \mathbf{z} \mid \mathbf{z} \in \mathcal{K}(T)} = \mathbf{u} + \mathcal{K}(T)$$

©2005, 2006 Robert A. Beezer

# Theorem KILT Kernel of an Injective Linear Transformation

286

Suppose that  $T: U \mapsto V$  is a linear transformation. Then T is injective if and only if the kernel of T is trivial,  $\mathcal{K}(T) = \{\mathbf{0}\}.$ 

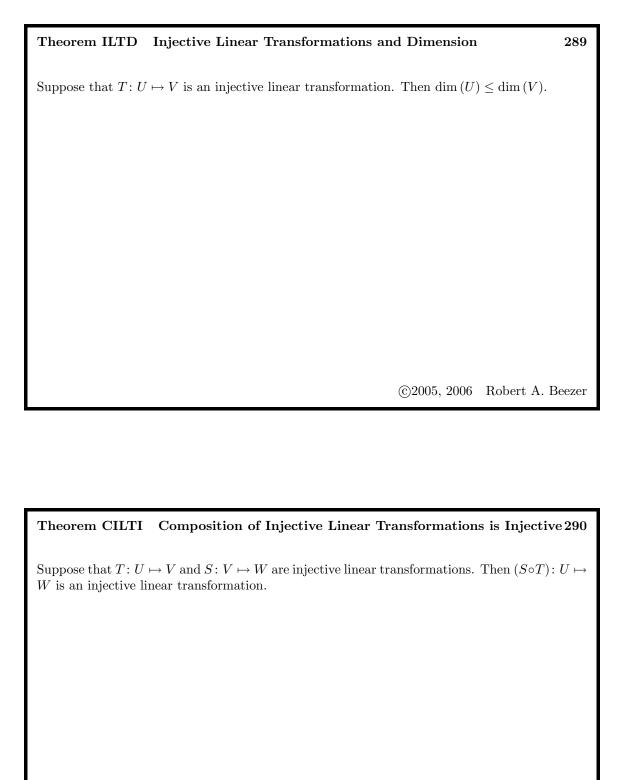


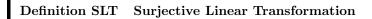
©2005, 2006 Robert A. Beezer

#### Theorem ILTB Injective Linear Transformations and Bases

288

Suppose that  $T: U \mapsto V$  is a linear transformation and  $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_m\}$  is a basis of U. Then T is injective if and only if  $C = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_m)\}$  is a linearly independent subset of V.





Suppose  $T: U \mapsto V$  is a linear transformation. Then T is **surjective** if for every  $\mathbf{v} \in V$  there exists a  $\mathbf{u} \in U$  so that  $T(\mathbf{u}) = \mathbf{v}$ .

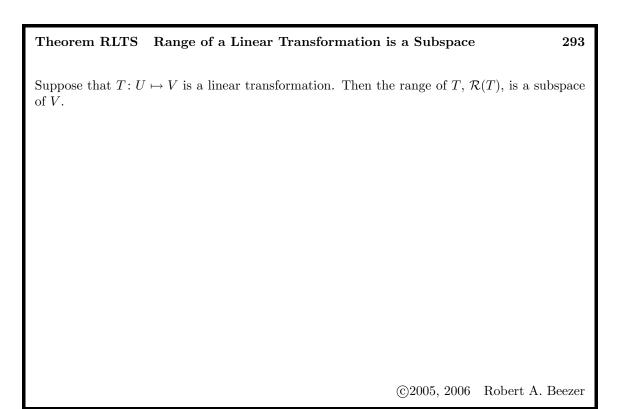
©2005, 2006 Robert A. Beezer

## Definition RLT Range of a Linear Transformation

292

Suppose  $T \colon U \mapsto V$  is a linear transformation. Then the **range** of T is the set

$$\mathcal{R}(T) = \{ T(\mathbf{u}) \mid \mathbf{u} \in U \}$$



# Theorem RSLT Range of a Surjective Linear Transformation

294

Suppose that  $T \colon U \mapsto V$  is a linear transformation. Then T is surjective if and only if the range of T equals the codomain,  $\mathcal{R}(T) = V$ .

# Theorem SSRLT Spanning Set for Range of a Linear Transformation

**295** 

Suppose that  $T: U \mapsto V$  is a linear transformation and  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$  spans U. Then

$$R = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), ..., T(\mathbf{u}_t)\}\$$

spans  $\mathcal{R}(T)$ .

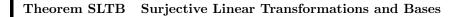
©2005, 2006 Robert A. Beezer

## Theorem RPI Range and Pre-Image

**296** 

Suppose that  $T \colon U \mapsto V$  is a linear transformation. Then

$$\mathbf{v} \in \mathcal{R}(T)$$
 if and only if  $T^{-1}(\mathbf{v}) \neq \emptyset$ 



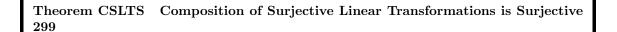
Suppose that  $T: U \mapsto V$  is a linear transformation and  $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_m\}$  is a basis of U. Then T is surjective if and only if  $C = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_m)\}$  is a spanning set for V.

©2005, 2006 Robert A. Beezer

## Theorem SLTD Surjective Linear Transformations and Dimension

298

Suppose that  $T \colon U \mapsto V$  is a surjective linear transformation. Then  $\dim(U) \ge \dim(V)$ .



Suppose that  $T\colon U\mapsto V$  and  $S\colon V\mapsto W$  are surjective linear transformations. Then  $(S\circ T)\colon U\mapsto W$  is a surjective linear transformation.

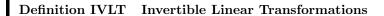
©2005, 2006 Robert A. Beezer

## Definition IDLT Identity Linear Transformation

300

The **identity linear transformation** on the vector space W is defined as

$$I_W \colon W \mapsto W, \qquad I_W (\mathbf{w}) = \mathbf{w}$$



Suppose that  $T: U \mapsto V$  is a linear transformation. If there is a function  $S: V \mapsto U$  such that

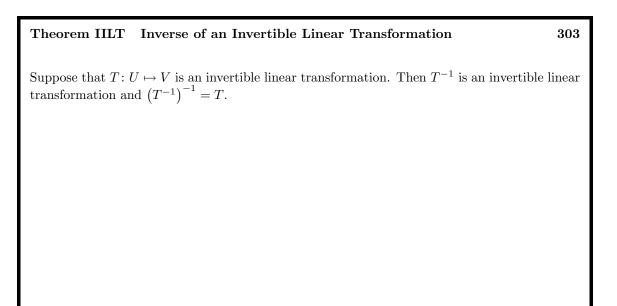
$$S \circ T = I_U \qquad \qquad T \circ S = I_V$$

then T is **invertible**. In this case, we call S the **inverse** of T and write  $S = T^{-1}$ .

© 2005, 2006 Robert A. Beezer

# Theorem ILTLT Inverse of a Linear Transformation is a Linear Transformation 302

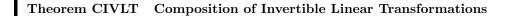
Suppose that  $T:U\mapsto V$  is an invertible linear transformation. Then the function  $T^{-1}:V\mapsto U$  is a linear transformation.



©2005, 2006 Robert A. Beezer

# Theorem ILTIS Invertible Linear Transformations are Injective and Surjective 304

Suppose  $T \colon U \mapsto V$  is a linear transformation. Then T is invertible if and only if T is injective and surjective.



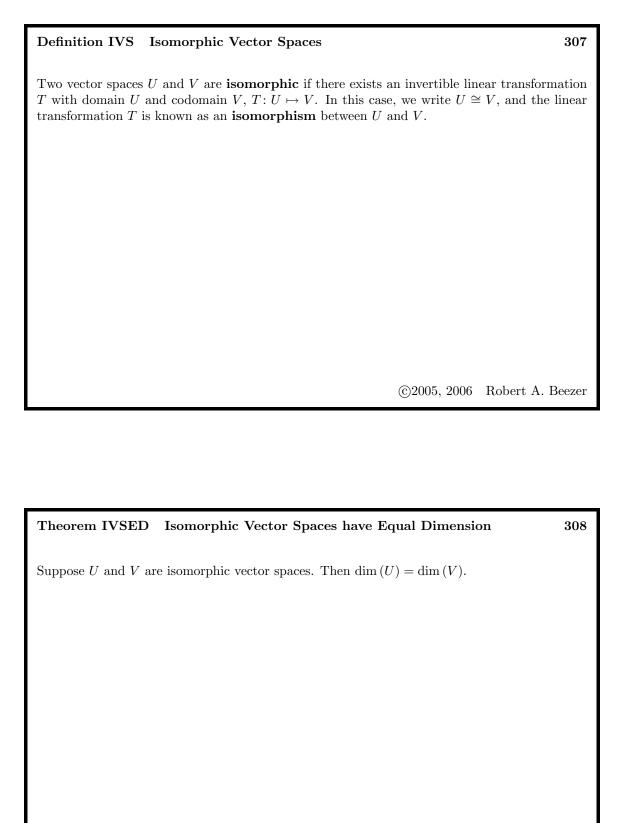
306

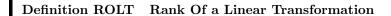
Suppose that  $T: U \mapsto V$  and  $S: V \mapsto W$  are invertible linear transformations. Then the composition,  $(S \circ T): U \mapsto W$  is an invertible linear transformation.

©2005, 2006 Robert A. Beezer

## Theorem ICLT Inverse of a Composition of Linear Transformations

Suppose that  $T\colon U\mapsto V$  and  $S\colon V\mapsto W$  are invertible linear transformations. Then  $S\circ T$  is invertible and  $\left(S\circ T\right)^{-1}=T^{-1}\circ S^{-1}$ .





Suppose that  $T:U\mapsto V$  is a linear transformation. Then the **rank** of T, r(T), is the dimension of the range of T,

$$r(T) = \dim (\mathcal{R}(T))$$

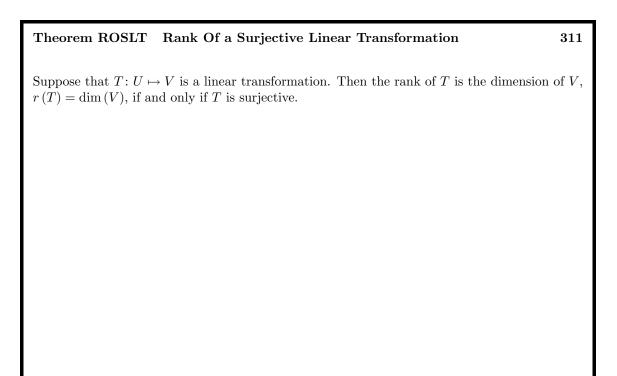
©2005, 2006 Robert A. Beezer

## Definition NOLT Nullity Of a Linear Transformation

310

Suppose that  $T:U\mapsto V$  is a linear transformation. Then the **nullity** of T, n(T), is the dimension of the kernel of T,

$$n(T) = \dim(\mathcal{K}(T))$$



# Theorem NOILT Nullity Of an Injective Linear Transformation

312

Suppose that  $T\colon U\mapsto V$  is an injective linear transformation. Then the nullity of T is zero,  $n\left(T\right)=0$ , if and only if T is injective.

©2005, 2006 Robert A. Beezer

## Theorem RPNDD Rank Plus Nullity is Domain Dimension

313

Suppose that  $T\colon U\mapsto V$  is a linear transformation. Then

$$r(T) + n(T) = \dim(U)$$

©2005, 2006 Robert A. Beezer

## Definition VR Vector Representation

314

Suppose that V is a vector space with a basis  $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$ . Define a function  $\rho_B \colon V \mapsto \mathbb{C}^n$  as follows. For  $\mathbf{w} \in V$ , find scalars  $a_1, a_2, a_3, \dots, a_n$  so that

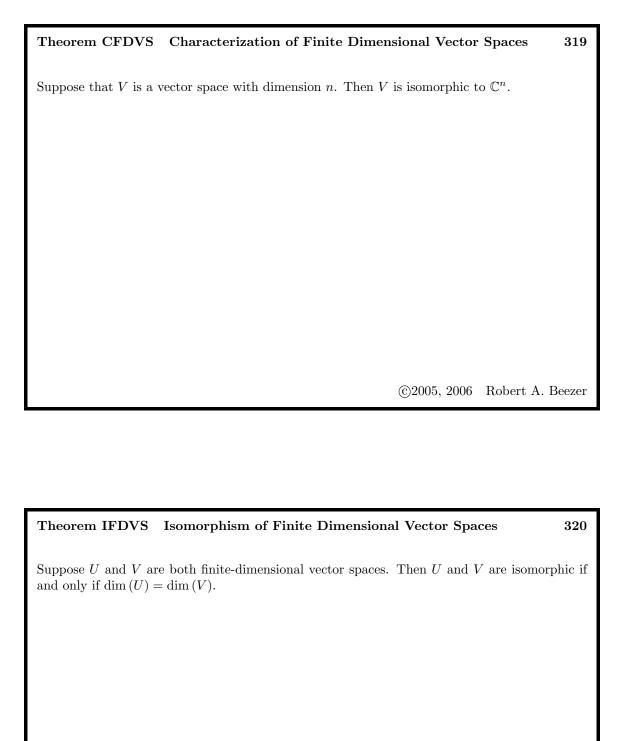
$$\mathbf{w} = a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2 + a_3 \mathbf{v}_3 + \dots + a_n \mathbf{v}_n$$

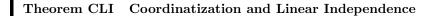
then

$$\left[\rho_B\left(\mathbf{w}\right)\right]_i = a_i \qquad \qquad 1 \le i \le n$$

Theorem VRLT	Vector Representation is a Linear	Transformation	on 315	
The function $\rho_B$ (D	efinition VR) is a linear transformation.			
		©2005, 2006	Robert A. Beezer	
Theorem VRI	Vector Representation is Injective		316	
The function $\rho_B$ (Definition VR) is an injective linear transformation.				

Theorem VRS Vector Representation is Surjective	317				
The function $\rho_B$ (Definition VR) is a surjective linear transformation.					
©2005, 2006	Robert A. Beezer				
Theorem VRILT Vector Representation is an Invertible Linear 318	Transformation				
The function $\rho_B$ (Definition VR) is an invertible linear transformation.					
©2005, 2006	Robert A. Beezer				





Suppose that U is a vector space with a basis B of size n. Then  $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_k\}$  is a linearly independent subset of U if and only if  $R = \{\rho_B(\mathbf{u}_1), \rho_B(\mathbf{u}_2), \rho_B(\mathbf{u}_3), \dots, \rho_B(\mathbf{u}_k)\}$  is a linearly independent subset of  $\mathbb{C}^n$ .

©2005, 2006 Robert A. Beezer

# Theorem CSS Coordinatization and Spanning Sets

322

Suppose that U is a vector space with a basis B of size n. Then  $\mathbf{u} \in \langle \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_k\} \rangle$  if and only if  $\rho_B(\mathbf{u}) \in \langle \{\rho_B(\mathbf{u}_1), \rho_B(\mathbf{u}_2), \rho_B(\mathbf{u}_3), \dots, \rho_B(\mathbf{u}_k)\} \rangle$ .

#### Definition MR Matrix Representation

323

Suppose that  $T: U \mapsto V$  is a linear transformation,  $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$  is a basis for U of size n, and C is a basis for V of size m. Then the **matrix representation** of T relative to B and C is the  $m \times n$  matrix,

$$M_{B,C}^{T} = \left[\rho_{C}\left(T\left(\mathbf{u}_{1}\right)\right)\middle|\rho_{C}\left(T\left(\mathbf{u}_{2}\right)\right)\middle|\rho_{C}\left(T\left(\mathbf{u}_{3}\right)\right)\middle|\dots\middle|\rho_{C}\left(T\left(\mathbf{u}_{n}\right)\right)\right]$$

© 2005, 2006 Robert A. Beezer

#### Theorem FTMR Fundamental Theorem of Matrix Representation

324

Suppose that  $T: U \mapsto V$  is a linear transformation, B is a basis for U, C is a basis for V and  $M_{B,C}^T$  is the matrix representation of T relative to B and C. Then, for any  $\mathbf{u} \in U$ ,

$$\rho_C\left(T\left(\mathbf{u}\right)\right) = M_{B,C}^T\left(\rho_B\left(\mathbf{u}\right)\right)$$

or equivalently

$$T\left(\mathbf{u}\right) = \rho_{C}^{-1}\left(M_{B,C}^{T}\left(\rho_{B}\left(\mathbf{u}\right)\right)\right)$$

# Theorem MRSLT Matrix Representation of a Sum of Linear Transformations 325

Suppose that  $T\colon U\mapsto V$  and  $S\colon U\mapsto V$  are linear transformations, B is a basis of U and C is a basis of V. Then

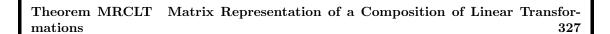
$$M_{B,C}^{T+S} = M_{B,C}^{T} + M_{B,C}^{S}$$

© 2005, 2006 Robert A. Beezer

# Theorem MRMLT Matrix Representation of a Multiple of a Linear Transformation 326

Suppose that  $T \colon U \mapsto V$  is a linear transformation,  $\alpha \in \mathbb{C}$ , B is a basis of U and C is a basis of V. Then

$$M_{B,C}^{\alpha T} = \alpha M_{B,C}^T$$



Suppose that  $T: U \mapsto V$  and  $S: V \mapsto W$  are linear transformations, B is a basis of U, C is a basis of V, and D is a basis of W. Then

$$M_{B,D}^{S \circ T} = M_{C,D}^S M_{B,C}^T$$

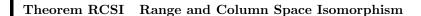
© 2005, 2006 Robert A. Beezer

## Theorem KNSI Kernel and Null Space Isomorphism

328

Suppose that  $T: U \mapsto V$  is a linear transformation, B is a basis for U of size n, and C is a basis for V. Then the kernel of T is isomorphic to the null space of  $M_{B,C}^T$ ,

$$\mathcal{K}(T) \cong \mathcal{N}(M_{B,C}^T)$$



Suppose that  $T: U \mapsto V$  is a linear transformation, B is a basis for U of size n, and C is a basis for V of size m. Then the range of T is isomorphic to the column space of  $M_{B,C}^T$ ,

$$\mathcal{R}(T) \cong \mathcal{C}(M_{B,C}^T)$$

© 2005, 2006 Robert A. Beezer

## Theorem IMR Invertible Matrix Representations

330

Suppose that  $T\colon U\mapsto V$  is an invertible linear transformation, B is a basis for U and C is a basis for V. Then the matrix representation of T relative to B and C,  $M_{B,C}^T$  is an invertible matrix, and

$$M_{C,B}^{T^{-1}} = \left(M_{B,C}^T\right)^{-1}$$

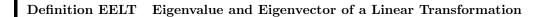
Suppose that A is a square matrix of size n and  $T: \mathbb{C}^n \to \mathbb{C}^n$  is the linear transformation defined by  $T(\mathbf{x}) = A\mathbf{x}$ . Then A is invertible matrix if and only if T is an invertible linear transformation.

© 2005, 2006 Robert A. Beezer

#### Theorem NME9 Nonsingular Matrix Equivalences, Round 9

Suppose that A is a square matrix of size n. The following are equivalent.

- 1. A is nonsingular.
- 2. A row-reduces to the identity matrix.
- 3. The null space of A contains only the zero vector,  $\mathcal{N}(A) = \{\mathbf{0}\}.$
- 4. The linear system  $\mathcal{LS}(A, \mathbf{b})$  has a unique solution for every possible choice of  $\mathbf{b}$ .
- 5. The columns of A are a linearly independent set.
- 6. A is invertible.
- 7. The column space of A is  $\mathbb{C}^n$ ,  $\mathcal{C}(A) = \mathbb{C}^n$ .
- 8. The columns of A are a basis for  $\mathbb{C}^n$ .
- 9. The rank of A is n, r(A) = n.
- 10. The nullity of A is zero, n(A) = 0.
- 11. The determinant of A is nonzero,  $\det(A) \neq 0$ .
- 12.  $\lambda = 0$  is not an eigenvalue of A.
- 13. The linear transformation  $T: \mathbb{C}^n \mapsto \mathbb{C}^n$  defined by  $T(\mathbf{x}) = A\mathbf{x}$  is invertible.



Suppose that  $T: V \mapsto V$  is a linear transformation. Then a nonzero vector  $\mathbf{v} \in V$  is an **eigenvector** of T for the **eigenvalue**  $\lambda$  if  $T(\mathbf{v}) = \lambda \mathbf{v}$ .

© 2005, 2006 Robert A. Beezer

#### Definition CBM Change-of-Basis Matrix

334

Suppose that V is a vector space, and  $I_V: V \mapsto V$  is the identity linear transformation on V. Let  $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$  and C be two bases of V. Then the **change-of-basis matrix** from B to C is the matrix representation of  $I_V$  relative to B and C,

$$C_{B,C} = M_{B,C}^{I_V}$$

$$= \left[ \rho_C \left( I_V \left( \mathbf{v}_1 \right) \right) \middle| \rho_C \left( I_V \left( \mathbf{v}_2 \right) \right) \middle| \rho_C \left( I_V \left( \mathbf{v}_3 \right) \right) \middle| \dots \middle| \rho_C \left( I_V \left( \mathbf{v}_n \right) \right) \right]$$

$$= \left[ \rho_C \left( \mathbf{v}_1 \right) \middle| \rho_C \left( \mathbf{v}_2 \right) \middle| \rho_C \left( \mathbf{v}_3 \right) \middle| \dots \middle| \rho_C \left( \mathbf{v}_n \right) \right]$$



Suppose that  $\mathbf{v}$  is a vector in the vector space V and B and C are bases of V. Then

$$\rho_C\left(\mathbf{v}\right) = C_{B,C}\rho_B\left(\mathbf{v}\right)$$

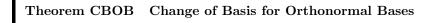
©2005, 2006 Robert A. Beezer

## Theorem ICBM Inverse of Change-of-Basis Matrix

336

Suppose that V is a vector space, and B and C are bases of V. Then the change-of-basis matrix  $C_{B,C}$  is nonsingular and

$$C_{B,C}^{-1} = C_{C,B}$$



Suppose that B and C are orthonormal bases for  $\mathbb{C}^n$ . Then the change-of-basis matrix,  $C_{B,C}$ , is a unitary matrix.

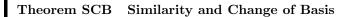
©2005, 2006 Robert A. Beezer

# Theorem MRCB Matrix Representation and Change of Basis

**338** 

Suppose that  $T\colon U\mapsto V$  is a linear transformation, B and C are bases for U, and D and E are bases for V. Then

$$M_{B,D}^T = C_{E,D} M_{C,E}^T C_{B,C}$$



Suppose that  $T: V \mapsto V$  is a linear transformation and B and C are bases of V. Then

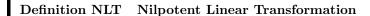
$$M_{B,B}^T = C_{B,C}^{-1} M_{C,C}^T C_{B,C}$$

©2005, 2006 Robert A. Beezer

## Theorem EER Eigenvalues, Eigenvectors, Representations

340

Suppose that  $T: V \mapsto V$  is a linear transformation and B is a basis of V. Then  $\mathbf{v} \in V$  is an eigenvector of T for the eigenvalue  $\lambda$  if and only if  $\rho_B(\mathbf{v})$  is an eigenvector of  $M_{B,B}^T$  for the eigenvalue  $\lambda$ .



Suppose that  $T: V \mapsto V$  is a linear transformation such that there is an integer p > 0 such that  $T^p(\mathbf{v}) = \mathbf{0}$  for every  $\mathbf{v} \in V$ . The smallest p for which this condition is met is called the **index** of T.

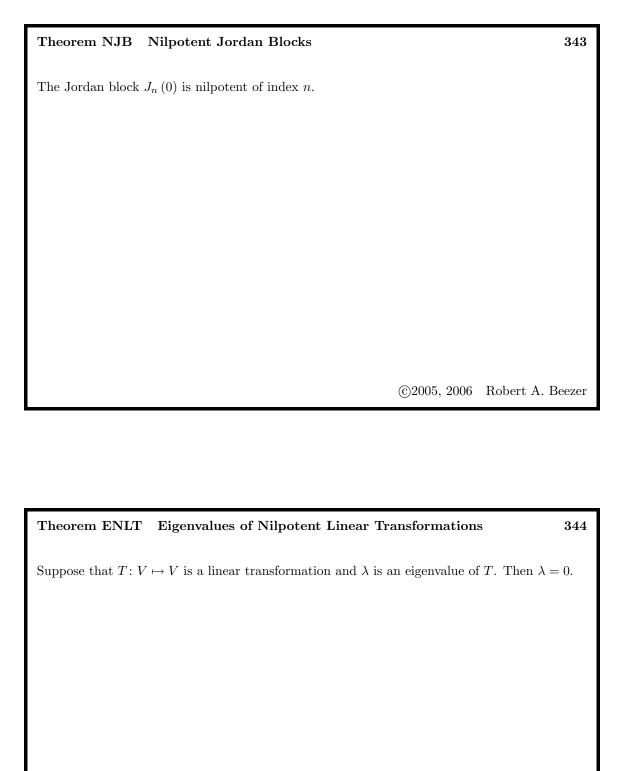
©2005, 2006 Robert A. Beezer

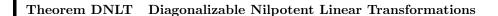
#### Definition JB Jordan Block

342

Given the scalar  $\lambda \in \mathbb{C}$ , the Jordan block  $J_n(\lambda)$  is the  $n \times n$  matrix defined by

$$\left[J_{n}\left(\lambda\right)\right]_{ij} = \begin{cases} \lambda & i = j\\ 1 & j = i+1\\ 0 & \text{otherwise} \end{cases}$$





Suppose the linear transformation  $T\colon V\mapsto V$  is nilpotent. Then T is diagonalizable if and only T is the zero linear transformation.

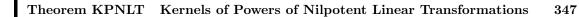
© 2005, 2006 Robert A. Beezer

#### Theorem KPLT Kernels of Powers of Linear Transformations

346

Suppose  $T: V \mapsto V$  is a linear transformation, where dim (V) = n. Then there is an integer m,  $0 \le m \le n$ , such that

$$\{\mathbf{0}\} = \mathcal{K}\big(T^0\big) \subsetneq \mathcal{K}\big(T^1\big) \subsetneq \mathcal{K}\big(T^2\big) \subsetneq \cdots \subsetneq \mathcal{K}(T^m) = \mathcal{K}\big(T^{m+1}\big) = \mathcal{K}\big(T^{m+2}\big) = \cdots$$



Suppose  $T: V \mapsto V$  is a nilpotent linear transformation with index p and dim (V) = n. Then  $0 \le p \le n$  and

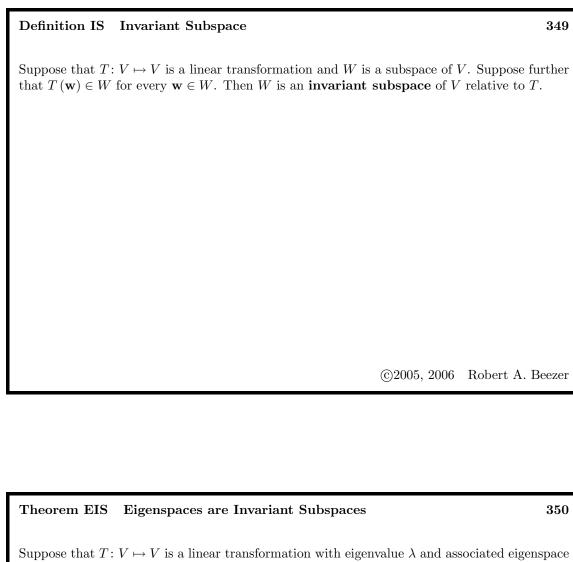
$$\{\mathbf{0}\} = \mathcal{K}(T^0) \subsetneq \mathcal{K}(T^1) \subsetneq \mathcal{K}(T^2) \subsetneq \cdots \subsetneq \mathcal{K}(T^p) = \mathcal{K}(T^{p+1}) = \cdots = V$$

© 2005, 2006 Robert A. Beezer

348

#### Theorem CFNLT Canonical Form for Nilpotent Linear Transformations

Suppose that  $T \colon V \mapsto V$  is a nilpotent linear transformation of index p. Then there is a basis for V so that the matrix representation,  $M_{B,B}^T$ , is block diagonal with each block being a Jordan block,  $J_n(0)$ . The size of the largest block is the index p, and the total number of blocks is the nullity of T, n(T).



Suppose that  $T: V \mapsto V$  is a linear transformation with eigenvalue  $\lambda$  and associated eigenspace  $\mathcal{E}_T(\lambda)$ . Let W be any subspace of  $\mathcal{E}_T(\lambda)$ . Then W is an invariant subspace of V relative to T.



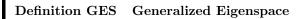
Suppose that  $T: V \mapsto V$  is a linear transformation. Then  $\mathcal{K}(T^k)$  is an invariant subspace of V.

©2005, 2006 Robert A. Beezer

# Definition GEV Generalized Eigenvector

352

Suppose that  $T: V \mapsto V$  is a linear transformation. Suppose further that for  $\mathbf{x} \neq \mathbf{0}$ ,  $(T - \lambda I_V)^k(\mathbf{x}) = \mathbf{0}$  for some k > 0. Then  $\mathbf{x}$  is a **generalized eigenvector** of T with eigenvalue  $\lambda$ .



Suppose that  $T: V \mapsto V$  is a linear transformation. Define the **generalized eigenspace** of T for  $\lambda$  as

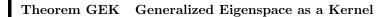
$$\mathcal{G}_{T}(\lambda) = \left\{ \mathbf{x} \mid \left(T - \lambda I_{V}\right)^{k}(\mathbf{x}) = \mathbf{0} \text{ for some } k \geq 0 \right\}$$

© 2005, 2006 Robert A. Beezer

## Theorem GESIS Generalized Eigenspace is an Invariant Subspace

354

Suppose that  $T: V \mapsto V$  is a linear transformation. Then the generalized eigenspace  $\mathcal{G}_{T}(\lambda)$  is an invariant subspace of V relative to T.



Suppose that  $T: V \mapsto V$  is a linear transformation,  $\dim(V) = n$ , and  $\lambda$  is an eigenvalue of T. Then  $\mathcal{G}_T(\lambda) = \mathcal{K}((T - \lambda I_V)^n)$ .

©2005, 2006 Robert A. Beezer

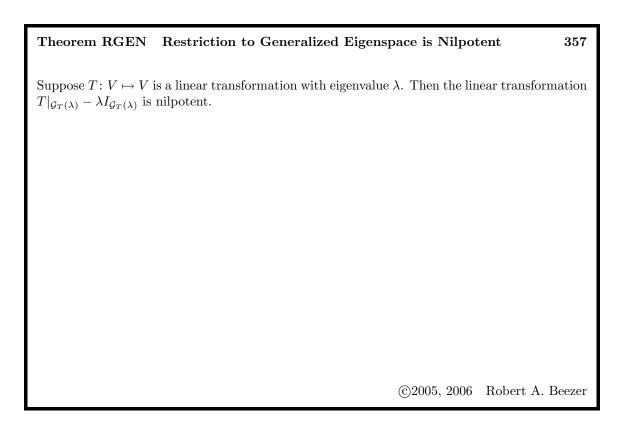
#### Definition LTR Linear Transformation Restriction

356

Suppose that  $T \colon V \mapsto V$  is a linear transformation, and U is an invariant subspace of V relative to T. Define the **restriction** of T to U by

$$T|_U \colon U \mapsto U$$

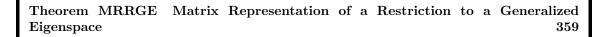
$$T|_{U}(\mathbf{u}) = T(\mathbf{u})$$



# Definition IE Index of an Eigenvalue

**358** 

Suppose  $T: V \mapsto V$  is a linear transformation with eigenvalue  $\lambda$ . Then the **index** of  $\lambda$ ,  $\iota_T(\lambda)$ , is the index of the nilpotent linear transformation  $T|_{\mathcal{G}_T(\lambda)} - \lambda I_{\mathcal{G}_T(\lambda)}$ .



Suppose that  $T: V \mapsto V$  is a linear transformation with eigenvalue  $\lambda$ . Then there is a basis of the the generalized eigenspace  $\mathcal{G}_T(\lambda)$  such that the restriction  $T|_{\mathcal{G}_T(\lambda)} \colon \mathcal{G}_T(\lambda) \mapsto \mathcal{G}_T(\lambda)$  has a matrix representation that is block diagonal where each block is a Jordan block of the form  $J_n(\lambda)$ .

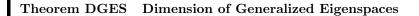
© 2005, 2006 Robert A. Beezer

# Theorem GESD Generalized Eigenspace Decomposition

360

Suppose that T(V)V is a linear transformation with distinct eigenvalues  $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_m$ . Then

$$V = \mathcal{G}_{T}(\lambda_{1}) \oplus \mathcal{G}_{T}(\lambda_{2}) \oplus \mathcal{G}_{T}(\lambda_{3}) \oplus \cdots \oplus \mathcal{G}_{T}(\lambda_{m})$$



Suppose  $T: V \mapsto V$  is a linear transformation with eigenvalue  $\lambda$ . Then the dimension of the generalized eigenspace for  $\lambda$  is the algebraic multiplicity of  $\lambda$ , dim  $(\mathcal{G}_T(\lambda_i)) = \alpha_T(\lambda_i)$ .

© 2005, 2006 Robert A. Beezer

#### Definition JCF Jordan Canonical Form

362

A square matrix is in **Jordan canonical form** if it meets the following requirements:

- 1. The matrix is block diagonal.
- 2. Each block is a Jordan block.
- 3. If  $\rho < \lambda$  then the block  $J_k(\rho)$  occupies rows with indices greater than the indices of the rows occupied by  $J_{\ell}(\lambda)$ .
- 4. If  $\rho = \lambda$  and  $\ell < k$ , then the block  $J_{\ell}(\lambda)$  occupies rows with indices greater than the indices of the rows occupied by  $J_{k}(\lambda)$ .

#### Theorem JCFLT Jordan Canonical Form for a Linear Transformation

363

Suppose  $T: V \mapsto V$  is a linear transformation. Then there is a basis B for V such that the matrix representation of T with the following properties:

- 1. The matrix representation is in Jordan canonical form.
- 2. If  $J_k(\lambda)$  is one of the Jordan blocks, then  $\lambda$  is an eigenvalue of T.
- 3. For a fixed value of  $\lambda$ , the largest block of the form  $J_k(\lambda)$  has size equal to the index of  $\lambda$ ,  $\iota_T(\lambda)$ .
- 4. For a fixed value of  $\lambda$ , the number of blocks of the form  $J_k(\lambda)$  is the geometric multiplicity of  $\lambda$ ,  $\gamma_T(\lambda)$ .
- 5. For a fixed value of  $\lambda$ , the number of rows occupied by blocks of the form  $J_k(\lambda)$  is the algebraic multiplicity of  $\lambda$ ,  $\alpha_T(\lambda)$ .

© 2005, 2006 Robert A. Beezer

#### Theorem CHT Cayley-Hamilton Theorem

364

Suppose A is a square matrix with characteristic polynomial  $p_{A}(x)$ . Then  $p_{A}(A) = \mathcal{O}$ .