

LINEAR ALGEBRA with Applications

Open Edition



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Adapted for

Emory University

Math 221

Linear Algebra

Sections 1 & 2 Lectured and adapted by

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Contents

1	Sys	tems of Linear Equations	5		
	1.1	Solutions and Elementary Operations	6		
	1.2	Gaussian Elimination	16		
	1.3	Homogeneous Equations	28		
	Sup	plementary Exercises for Chapter 1	37		
2	Ma	trix Algebra	39		
	2.1	Matrix Addition, Scalar Multiplication, and Transposition	40		
	2.2	Matrix-Vector Multiplication	53		
	2.3	Matrix Multiplication	72		
	2.4	Matrix Inverses	91		
	2.5	Elementary Matrices	109		
	2.6	Linear Transformations	119		
	2.7	LU-Factorization	135		
3	Determinants and Diagonalization				
	3.1	The Cofactor Expansion	148		
	3.2	Determinants and Matrix Inverses	163		
	3.3	Diagonalization and Eigenvalues	178		
	Sup	plementary Exercises for Chapter 3	201		
4	Vec	tor Geometry	203		
	4.1	Vectors and Lines	204		
	4.2	Projections and Planes	223		
	4.3	More on the Cross Product	244		
	4.4	Linear Operators on \mathbb{R}^3	251		
	Sup	plementary Exercises for Chapter 4	260		
5	Vector Space \mathbb{R}^n 26				
	5.1	Subspaces and Spanning	264		
	5.2	Independence and Dimension	273		
	5.3	Orthogonality	287		
	5.4	Rank of a Matrix	297		

$4 \equiv \text{CONTENTS}$

	5.5	Similarity and Diagonalization)7
	Supp	plementary Exercises for Chapter 5	20
6	Vec	tor Spaces 32	!1
	6.1	Examples and Basic Properties	22
	6.2	Subspaces and Spanning Sets	33
	6.3	Linear Independence and Dimension	12
	6.4	Finite Dimensional Spaces	54
	Supp	plementary Exercises for Chapter $6 \ldots 36$	34
7	Line	ear Transformations 36	65
	7.1	Examples and Elementary Properties	36
	7.2	Kernel and Image of a Linear Transformation	74
	7.3	Isomorphisms and Composition	35
8	Ort	hogonality 39	9
	8.1	Orthogonal Complements and Projections)()
	8.2	Orthogonal Diagonalization	10
	8.3	Positive Definite Matrices	21
	8.4	QR-Factorization	27
	8.5	Computing Eigenvalues	31
	8.6	The Singular Value Decomposition	36
		8.6.1 Singular Value Decompositions	36
		8.6.2 Fundamental Subspaces	12
		8.6.3 The Polar Decomposition of a Real Square Matrix	15
		8.6.4 The Pseudoinverse of a Matrix	17

5.2 Independence and Dimension

Some spanning sets are better than others. If $U = \text{span} \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\}$ is a subspace of \mathbb{R}^n , then every vector in U can be written as a linear combination of the \mathbf{x}_i in at least one way. Our interest here is in spanning sets where each vector in U has a *exactly one* representation as a linear combination of these vectors.

Linear Independence

Given $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k$ in \mathbb{R}^n , suppose that two linear combinations are equal:

 $r_1\mathbf{x}_1 + r_2\mathbf{x}_2 + \dots + r_k\mathbf{x}_k = s_1\mathbf{x}_1 + s_2\mathbf{x}_2 + \dots + s_k\mathbf{x}_k$

We are looking for a condition on the set $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k\}$ of vectors that guarantees that this representation is *unique*; that is, $r_i = s_i$ for each *i*. Taking all terms to the left side gives

$$(r_1 - s_1)\mathbf{x}_1 + (r_2 - s_2)\mathbf{x}_2 + \dots + (r_k - s_k)\mathbf{x}_k = \mathbf{0}$$

so the required condition is that this equation forces all the coefficients $r_i - s_i$ to be zero.

Definition 5.3 Linear Independence in \mathbb{R}^n

With this in mind, we call a set $\{x_1, x_2, ..., x_k\}$ of vectors **linearly independent** (or simply **independent**) if it satisfies the following condition:

If
$$t_1 \mathbf{x}_1 + t_2 \mathbf{x}_2 + \dots + t_k \mathbf{x}_k = \mathbf{0}$$
 then $t_1 = t_2 = \dots = t_k = 0$

We record the result of the above discussion for reference.

Theorem 5.2.1

```
If \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k\} is an independent set of vectors in \mathbb{R}^n, then every vector in span \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k\} has a unique representation as a linear combination of the \mathbf{x}_i.
```

It is useful to state the definition of independence in different language. Let us say that a linear combination **vanishes** if it equals the zero vector, and call a linear combination **trivial** if every coefficient is zero. Then the definition of independence can be compactly stated as follows:

A set of vectors is independent if and only if the only linear combination that vanishes is the trivial one.

Hence we have a procedure for checking that a set of vectors is independent:

Independence Test

To verify that a set $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ of vectors in \mathbb{R}^n is independent, proceed as follows:

1. Set a linear combination equal to zero: $t_1\mathbf{x}_1 + t_2\mathbf{x}_2 + \cdots + t_k\mathbf{x}_k = \mathbf{0}$.

2. Show that $t_i = 0$ for each *i* (that is, the linear combination is trivial).

Of course, if some nontrivial linear combination vanishes, the vectors are not independent.

Example 5.2.1

Determine whether $\{(1, 0, -2, 5), (2, 1, 0, -1), (1, 1, 2, 1)\}$ is independent in \mathbb{R}^4 .

Solution. Suppose a linear combination vanishes:

r(1, 0, -2, 5) + s(2, 1, 0, -1) + t(1, 1, 2, 1) = (0, 0, 0, 0)

Equating corresponding entries gives a system of four equations:

r+2s+t=0, s+t=0, -2r+2t=0, and 5r-s+t=0

The only solution is the trivial one r = s = t = 0 (verify), so these vectors are independent by the independence test.

Example 5.2.2

Show that the standard basis $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$ of \mathbb{R}^n is independent.

<u>Solution</u>. The components of $t_1\mathbf{e}_1 + t_2\mathbf{e}_2 + \cdots + t_n\mathbf{e}_n$ are t_1, t_2, \ldots, t_n (see the discussion preceding Example 5.1.6) So the linear combination vanishes if and only if each $t_i = 0$. Hence the independence test applies.

Example 5.2.3

If $\{x, y\}$ is independent, show that $\{2x + 3y, x - 5y\}$ is also independent.

Solution. If $s(2\mathbf{x}+3\mathbf{y})+t(\mathbf{x}-5\mathbf{y})=\mathbf{0}$, collect terms to get $(2s+t)\mathbf{x}+(3s-5t)\mathbf{y}=\mathbf{0}$. Since $\{\mathbf{x}, \mathbf{y}\}$ is independent this combination must be trivial; that is, 2s+t=0 and 3s-5t=0. These equations have only the trivial solution s=t=0, as required.

Example 5.2.4

Show that the zero vector in \mathbb{R}^n does not belong to any independent set.

Solution. No set $\{0, x_1, x_2, ..., x_k\}$ of vectors is independent because we have a vanishing, nontrivial linear combination $1 \cdot 0 + 0x_1 + 0x_2 + \cdots + 0x_k = 0$.

Example 5.2.5

Given \mathbf{x} in \mathbb{R}^n , show that $\{\mathbf{x}\}$ is independent if and only if $\mathbf{x} \neq \mathbf{0}$.

Solution. A vanishing linear combination from $\{\mathbf{x}\}$ takes the form $t\mathbf{x} = \mathbf{0}, t$ in \mathbb{R} . This implies that t = 0 because $\mathbf{x} \neq \mathbf{0}$.

The next example will be needed later.

Example 5.2.6

Show that the nonzero rows of a row-echelon matrix R are independent.

Solution. We illustrate the case with 3 leading 1s; the general case is analogous. Suppose R has the form $R = \begin{bmatrix} 0 & 1 & * & * & * & * \\ 0 & 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 1 & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ where * indicates a nonspecified number. Let R_1 , R_2 , and R_3 denote the nonzero rows of R. If $t_1R_1 + t_2R_2 + t_3R_3 = 0$ we show that $t_1 = 0$, then

 R_2 , and R_3 denote the nonzero rows of R. If $t_1R_1 + t_2R_2 + t_3R_3 = 0$ we show that $t_1 = 0$, then $t_2 = 0$, and finally $t_3 = 0$. The condition $t_1R_1 + t_2R_2 + t_3R_3 = 0$ becomes

 $(0, t_1, *, *, *, *) + (0, 0, 0, t_2, *, *) + (0, 0, 0, 0, t_3, *) = (0, 0, 0, 0, 0, 0)$

Equating second entries show that $t_1 = 0$, so the condition becomes $t_2R_2 + t_3R_3 = 0$. Now the same argument shows that $t_2 = 0$. Finally, this gives $t_3R_3 = 0$ and we obtain $t_3 = 0$.

A set of vectors in \mathbb{R}^n is called **linearly dependent** (or simply **dependent**) if it is *not* linearly independent, equivalently if some nontrivial linear combination vanishes.

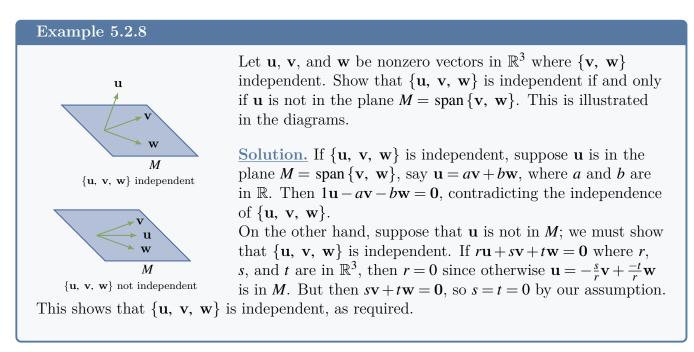
Example 5.2.7

If \mathbf{v} and \mathbf{w} are nonzero vectors in \mathbb{R}^3 , show that $\{\mathbf{v}, \mathbf{w}\}$ is dependent if and only if \mathbf{v} and \mathbf{w} are parallel.

Solution. If **v** and **w** are parallel, then one is a scalar multiple of the other (Theorem 4.1.4), say $\mathbf{v} = a\mathbf{w}$ for some scalar a. Then the nontrivial linear combination $\mathbf{v} - a\mathbf{w} = \mathbf{0}$ vanishes, so $\{\mathbf{v}, \mathbf{w}\}$ is dependent. Conversely, if $\{\mathbf{v}, \mathbf{w}\}$ is dependent, let $s\mathbf{v} + t\mathbf{w} = \mathbf{0}$ be nontrivial, say $s \neq 0$. Then $\mathbf{v} = -\frac{t}{s}\mathbf{w}$ so **v** and **w** are parallel (by Theorem 4.1.4). A similar argument works if $t \neq 0$.

With this we can give a geometric description of what it means for a set $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ in \mathbb{R}^3 to be independent. Note that this requirement means that $\{\mathbf{v}, \mathbf{w}\}$ is also independent $(a\mathbf{v} + b\mathbf{w} = \mathbf{0})$

means that $0\mathbf{u} + a\mathbf{v} + b\mathbf{w} = \mathbf{0}$, so $M = \text{span}\{\mathbf{v}, \mathbf{w}\}$ is the plane containing \mathbf{v}, \mathbf{w} , and $\mathbf{0}$ (see the discussion preceding Example 5.1.4). So we assume that $\{\mathbf{v}, \mathbf{w}\}$ is independent in the following example.



By the inverse theorem, the following conditions are equivalent for an $n \times n$ matrix A:

- 1. A is invertible.
- 2. If $A\mathbf{x} = \mathbf{0}$ where \mathbf{x} is in \mathbb{R}^n , then $\mathbf{x} = \mathbf{0}$.
- 3. $A\mathbf{x} = \mathbf{b}$ has a solution \mathbf{x} for every vector \mathbf{b} in \mathbb{R}^n .

While condition 1 makes no sense if A is not square, conditions 2 and 3 are meaningful for any matrix A and, in fact, are related to independence and spanning. Indeed, if c_1, c_2, \ldots, c_n are the

While contained matrix A and, in fact, are noted to be a contained of A, and if we write $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$, then $A\mathbf{x} = x_1\mathbf{c}_1 + x_2\mathbf{c}_2 + \dots + x_n$

by Definition 2.5. Hence the definitions of independence and spanning show, respectively, that condition 2 is equivalent to the independence of $\{c_1, c_2, ..., c_n\}$ and condition 3 is equivalent to the requirement that span $\{c_1, c_2, \ldots, c_n\} = \mathbb{R}^m$. This discussion is summarized in the following theorem:

Theorem 5.2.2

If A is an $m \times n$ matrix, let $\{c_1, c_2, \ldots, c_n\}$ denote the columns of A.

1. $\{c_1, c_2, \ldots, c_n\}$ is independent in \mathbb{R}^m if and only if $A\mathbf{x} = \mathbf{0}$, \mathbf{x} in \mathbb{R}^n , implies $\mathbf{x} = \mathbf{0}$.

2. $\mathbb{R}^m = \text{span} \{ c_1, c_2, \dots, c_n \}$ if and only if $A\mathbf{x} = \mathbf{b}$ has a solution \mathbf{x} for every vector \mathbf{b} in \mathbb{R}^m .

For a square matrix A, Theorem 5.2.2 characterizes the invertibility of A in terms of the spanning and independence of its columns (see the discussion preceding Theorem 5.2.2). It is important to be able to discuss these notions for rows. If $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k$ are $1 \times n$ rows, we define span $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ to be the set of all linear combinations of the \mathbf{x}_i (as matrices), and we say that $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ is linearly independent if the only vanishing linear combination is the trivial one (that is, if $\{\mathbf{x}_1^T, \mathbf{x}_2^T, \ldots, \mathbf{x}_k^T\}$ is independent in \mathbb{R}^n , as the reader can verify).⁶

Theorem 5.2.3

The following are equivalent for an $n \times n$ matrix A:

- 1. A is invertible.
- 2. The columns of A are linearly independent.
- 3. The columns of A span \mathbb{R}^n .
- 4. The rows of A are linearly independent.
- 5. The rows of A span the set of all $1 \times n$ rows.

Proof. Let $\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_n$ denote the columns of A.

(1) \Leftrightarrow (2). By Theorem 2.4.5, A is invertible if and only if $A\mathbf{x} = \mathbf{0}$ implies $\mathbf{x} = \mathbf{0}$; this holds if and only if $\{\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_n\}$ is independent by Theorem 5.2.2.

(1) \Leftrightarrow (3). Again by Theorem 2.4.5, A is invertible if and only if $A\mathbf{x} = \mathbf{b}$ has a solution for every column B in \mathbb{R}^n ; this holds if and only if span { $\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_n$ } = \mathbb{R}^n by Theorem 5.2.2.

(1) \Leftrightarrow (4). The matrix A is invertible if and only if A^T is invertible (by Corollary 2.4.1 to Theorem 2.4.4); this in turn holds if and only if A^T has independent columns (by (1) \Leftrightarrow (2)); finally, this last statement holds if and only if A has independent rows (because the rows of A are the transposes of the columns of A^T).

(1) \Leftrightarrow (5). The proof is similar to (1) \Leftrightarrow (4).

Example 5.2.9

Show that $S = \{(2, -2, 5), (-3, 1, 1), (2, 7, -4)\}$ is independent in \mathbb{R}^3 . Solution. Consider the matrix $A = \begin{bmatrix} 2 & -2 & 5 \\ -3 & 1 & 1 \\ 2 & 7 & -4 \end{bmatrix}$ with the vectors in S as its rows. A routine computation shows that $\det A = -117 \neq 0$, so A is invertible. Hence S is independent by Theorem 5.2.3. Note that Theorem 5.2.3 also shows that $\mathbb{R}^3 = \operatorname{span} S$.

 $^{^{6}}$ It is best to view columns and rows as just two different *notations* for ordered *n*-tuples. This discussion will become redundant in Chapter 6 where we define the general notion of a vector space.

Dimension

It is common geometrical language to say that \mathbb{R}^3 is 3-dimensional, that planes are 2-dimensional and that lines are 1-dimensional. The next theorem is a basic tool for clarifying this idea of "dimension". Its importance is difficult to exaggerate.

Theorem 5.2.4: Fundamental Theorem

Let U be a subspace of \mathbb{R}^n . If U is spanned by m vectors, and if U contains k linearly independent vectors, then $k \leq m$.

This proof is given in Theorem 6.3.2 in much greater generality.

Definition 5.4 Basis of \mathbb{R}^n

If U is a subspace of \mathbb{R}^n , a set $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m\}$ of vectors in U is called a **basis** of U if it satisfies the following two conditions:

1. $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m\}$ is linearly independent.

2. $U = \text{span} \{ \mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_m \}.$

The most remarkable result about bases⁷ is:

Theorem 5.2.5: Invariance Theorem

If $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m\}$ and $\{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_k\}$ are bases of a subspace U of \mathbb{R}^n , then m = k.

Proof. We have $k \leq m$ by the fundamental theorem because $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m\}$ spans U, and $\{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_k\}$ is independent. Similarly, by interchanging \mathbf{x} 's and \mathbf{y} 's we get $m \leq k$. Hence m = k.

The invariance theorem guarantees that there is no ambiguity in the following definition:

Definition 5.5 Dimension of a Subspace of \mathbb{R}^n

If U is a subspace of \mathbb{R}^n and $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m\}$ is any basis of U, the number, m, of vectors in the basis is called the **dimension** of U, denoted

dim U = m

The importance of the invariance theorem is that the dimension of U can be determined by counting the number of vectors in *any* basis.⁸

⁷The plural of "basis" is "bases".

⁸We will show in Theorem 5.2.6 that every subspace of \mathbb{R}^n does indeed have a basis.

Let $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ denote the standard basis of \mathbb{R}^n , that is the set of columns of the identity matrix. Then $\mathbb{R}^n = \operatorname{span} \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ by Example 5.1.6, and $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is independent by Example 5.2.2. Hence it is indeed a basis of \mathbb{R}^n in the present terminology, and we have

Example 5.2.10	
$\dim (\mathbb{R}^n) = n$ and $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is a basis.	

This agrees with our geometric sense that \mathbb{R}^2 is two-dimensional and \mathbb{R}^3 is three-dimensional. It also says that $\mathbb{R}^1 = \mathbb{R}$ is one-dimensional, and $\{1\}$ is a basis. Returning to subspaces of \mathbb{R}^n , we define

$$\dim \{0\} = 0$$

This amounts to saying $\{0\}$ has a basis containing *no* vectors. This makes sense because **0** cannot belong to *any* independent set (Example 5.2.4).

Example 5.2.11

Let $U = \left\{ \begin{bmatrix} r \\ s \\ r \end{bmatrix} \mid r, s \text{ in } \mathbb{R} \right\}$. Show that U is a subspace of \mathbb{R}^3 , find a basis, and calculate dim U. Solution. Clearly, $\begin{bmatrix} r \\ s \\ r \end{bmatrix} = r\mathbf{u} + s\mathbf{v}$ where $\mathbf{u} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ and $\mathbf{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$. It follows that $U = span \{\mathbf{u}, \mathbf{v}\}$, and hence that U is a subspace of \mathbb{R}^3 . Moreover, if $r\mathbf{u} + s\mathbf{v} = \mathbf{0}$, then $\begin{bmatrix} r \\ s \\ r \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$ so r = s = 0. Hence $\{\mathbf{u}, \mathbf{v}\}$ is independent, and so a **basis** of U. This means dim U = 2.

Example 5.2.12

Let $B = {\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n}$ be a basis of \mathbb{R}^n . If A is an invertible $n \times n$ matrix, then $D = {A\mathbf{x}_1, A\mathbf{x}_2, ..., A\mathbf{x}_n}$ is also a basis of \mathbb{R}^n .

Solution. Let **x** be a vector in \mathbb{R}^n . Then $A^{-1}\mathbf{x}$ is in \mathbb{R}^n so, since **B** is a basis, we have $A^{-1}\mathbf{x} = t_1\mathbf{x}_1 + t_2\mathbf{x}_2 + \cdots + t_n\mathbf{x}_n$ for t_i in \mathbb{R} . Left multiplication by **A** gives $\mathbf{x} = t_1(A\mathbf{x}_1) + t_2(A\mathbf{x}_2) + \cdots + t_n(A\mathbf{x}_n)$, and it follows that **D** spans \mathbb{R}^n . To show independence, let $s_1(A\mathbf{x}_1) + s_2(A\mathbf{x}_2) + \cdots + s_n(A\mathbf{x}_n) = \mathbf{0}$, where the s_i are in \mathbb{R} . Then $A(s_1\mathbf{x}_1 + s_2\mathbf{x}_2 + \cdots + s_n\mathbf{x}_n) = \mathbf{0}$ so left multiplication by A^{-1} gives $s_1\mathbf{x}_1 + s_2\mathbf{x}_2 + \cdots + s_n\mathbf{x}_n = \mathbf{0}$. Now the independence of **B** shows that each $s_i = \mathbf{0}$, and so proves the independence of **D**. Hence **D** is a basis of \mathbb{R}^n .

While we have found bases in many subspaces of \mathbb{R}^n , we have not yet shown that *every* subspace *has* a basis. This is part of the next theorem, the proof of which is deferred to Section 6.4 (Theorem 6.4.1) where it will be proved in more generality.

Theorem 5.2.6

Let $U \neq \{0\}$ be a subspace of \mathbb{R}^n . Then:

- 1. U has a basis and dim $U \leq n$.
- 2. Any independent set in U can be enlarged (by adding vectors from the standard basis) to a basis of U.
- 3. Any spanning set for U can be cut down (by deleting vectors) to a basis of U.

Example 5.2.13

Find a basis of \mathbb{R}^4 containing $S = \{\mathbf{u}, \mathbf{v}\}$ where $\mathbf{u} = (0, 1, 2, 3)$ and $\mathbf{v} = (2, -1, 0, 1)$.

Solution. By Theorem 5.2.6 we can find such a basis by adding vectors from the standard basis of \mathbb{R}^4 to S. If we try $\mathbf{e}_1 = (1, 0, 0, 0)$, we find easily that $\{\mathbf{e}_1, \mathbf{u}, \mathbf{v}\}$ is independent. Now add another vector from the standard basis, say \mathbf{e}_2 . Again we find that $B = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{u}, \mathbf{v}\}$ is independent. Since B has $4 = \dim \mathbb{R}^4$ vectors, then B must span \mathbb{R}^4 by Theorem 5.2.7 below (or simply verify it directly). Hence B is a basis of \mathbb{R}^4 .

Theorem 5.2.6 has a number of useful consequences. Here is the first.

Theorem 5.2.7

Let U be a subspace of \mathbb{R}^n where dim U = m and let $B = \{x_1, x_2, \ldots, x_m\}$ be a set of m vectors in U. Then B is independent if and only if B spans U.

Proof. Suppose *B* is independent. If *B* does not span *U* then, by Theorem 5.2.6, *B* can be enlarged to a basis of *U* containing more than *m* vectors. This contradicts the invariance theorem because $\dim U = m$, so *B* spans *U*. Conversely, if *B* spans *U* but is not independent, then *B* can be cut down to a basis of *U* containing fewer than *m* vectors, again a contradiction. So *B* is independent, as required.

As we saw in Example 5.2.13, Theorem 5.2.7 is a "labour-saving" result. It asserts that, given a subspace U of dimension m and a set B of exactly m vectors in U, to prove that B is a basis of U it suffices to show either that B spans U or that B is independent. It is not necessary to verify both properties.

Theorem 5.2.8

Let $U \subseteq W$ be subspaces of \mathbb{R}^n . Then:

- 1. dim $U \leq \dim W$.
- 2. If dim $U = \dim W$, then U = W.

Proof. Write dim W = k, and let **B** be a basis of **U**.

- 1. If dim U > k, then B is an independent set in W containing more than k vectors, contradicting the fundamental theorem. So dim $U \le k = \dim W$.
- 2. If dim U = k, then B is an independent set in W containing $k = \dim W$ vectors, so B spans W by Theorem 5.2.7. Hence $W = \operatorname{span} B = U$, proving (2).

It follows from Theorem 5.2.8 that if U is a subspace of \mathbb{R}^n , then dim U is one of the integers 0, 1, 2, ..., n, and that:

dim
$$U = 0$$
 if and only if $U = \{0\}$,
dim $U = n$ if and only if $U = \mathbb{R}^n$

The other subspaces of \mathbb{R}^n are called **proper**. The following example uses Theorem 5.2.8 to show that the proper subspaces of \mathbb{R}^2 are the lines through the origin, while the proper subspaces of \mathbb{R}^3 are the lines and planes through the origin.

Example 5.2.14

- 1. If U is a subspace of \mathbb{R}^2 or \mathbb{R}^3 , then dim U = 1 if and only if U is a line through the origin.
- 2. If U is a subspace of \mathbb{R}^3 , then dim U = 2 if and only if U is a plane through the origin.

Proof.

- 1. Since dim U = 1, let $\{\mathbf{u}\}$ be a basis of U. Then $U = \operatorname{span} \{\mathbf{u}\} = \{t\mathbf{u} \mid t \text{ in } \mathbb{R}\}$, so U is the line through the origin with direction vector \mathbf{u} . Conversely each line L with direction vector $\mathbf{d} \neq \mathbf{0}$ has the form $L = \{t\mathbf{d} \mid t \text{ in } \mathbb{R}\}$. Hence $\{\mathbf{d}\}$ is a basis of U, so U has dimension 1.
- 2. If $U \subseteq \mathbb{R}^3$ has dimension 2, let $\{\mathbf{v}, \mathbf{w}\}$ be a basis of U. Then \mathbf{v} and \mathbf{w} are not parallel (by Example 5.2.7) so $\mathbf{n} = \mathbf{v} \times \mathbf{w} \neq \mathbf{0}$. Let $P = \{\mathbf{x} \text{ in } \mathbb{R}^3 \mid \mathbf{n} \cdot \mathbf{x} = \mathbf{0}\}$ denote the plane through the origin with normal \mathbf{n} . Then P is a subspace of \mathbb{R}^3 (Example 5.1.1) and both \mathbf{v} and \mathbf{w} lie in P (they are orthogonal to \mathbf{n}), so $U = \text{span}\{\mathbf{v}, \mathbf{w}\} \subseteq P$ by Theorem 5.1.1. Hence

$$U \subseteq P \subseteq \mathbb{R}^3$$

Since dim U = 2 and dim $(\mathbb{R}^3) = 3$, it follows from Theorem 5.2.8 that dim P = 2 or 3, whence P = U or \mathbb{R}^3 . But $P \neq \mathbb{R}^3$ (for example, **n** is not in *P*) and so U = P is a plane through the origin.

Conversely, if U is a plane through the origin, then dim U = 0, 1, 2, or 3 by Theorem 5.2.8. But dim $U \neq 0$ or 3 because $U \neq \{0\}$ and $U \neq \mathbb{R}^3$, and dim $U \neq 1$ by (1). So dim U = 2.

Note that this proof shows that if \mathbf{v} and \mathbf{w} are nonzero, nonparallel vectors in \mathbb{R}^3 , then span $\{\mathbf{v}, \mathbf{w}\}$ is the plane with normal $\mathbf{n} = \mathbf{v} \times \mathbf{w}$. We gave a geometrical verification of this fact in Section 5.1.

Exercises for 5.2

In Exercises 5.2.1-5.2.6 we write vectors \mathbb{R}^n as rows.

Exercise 5.2.1 Which of the following subsets are independent? Support your answer.

- a. $\{(1, -1, 0), (3, 2, -1), (3, 5, -2)\}$ in \mathbb{R}^3
- b. {(1, 1, 1), (1, -1, 1), (0, 0, 1)} in \mathbb{R}^3
- c. {(1, -1, 1, -1), (2, 0, 1, 0), (0, -2, 1, -2)} in \mathbb{R}^4
- d. {(1, 1, 0, 0), (1, 0, 1, 0), (0, 0, 1, 1), (0, 1, 0, 1)} in \mathbb{R}^4
- b. Yes. If $r \begin{bmatrix} 1\\1\\1 \end{bmatrix} + s \begin{bmatrix} 1\\1\\1 \end{bmatrix} + t \begin{bmatrix} 0\\0\\1 \end{bmatrix} = \begin{bmatrix} 0\\0\\0 \end{bmatrix}$, then r+s=0, r-s=0, and r+s+t=0. These equations give r=s=t=0.

d. No. Indeed:
$$\begin{bmatrix} 1\\1\\0\\0 \end{bmatrix} - \begin{bmatrix} 1\\0\\1\\0 \end{bmatrix} + \begin{bmatrix} 0\\0\\1\\1 \end{bmatrix} - \begin{bmatrix} 0\\1\\1 \end{bmatrix} = \begin{bmatrix} 0\\0\\0\\0 \end{bmatrix}.$$

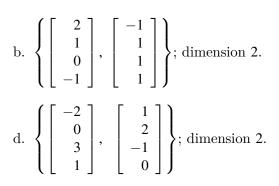
Exercise 5.2.2 Let $\{\mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{w}\}$ be an independent set in \mathbb{R}^n . Which of the following sets is independent? Support your answer.

- a. $\{x y, y z, z x\}$
- b. $\{\mathbf{x} + \mathbf{y}, \mathbf{y} + \mathbf{z}, \mathbf{z} + \mathbf{x}\}$
- c. $\{x y, y z, z w, w x\}$
- d. { $\mathbf{x} + \mathbf{y}, \mathbf{y} + \mathbf{z}, \mathbf{z} + \mathbf{w}, \mathbf{w} + \mathbf{x}$ }

- b. Yes. If $r(\mathbf{x} + \mathbf{y}) + s(\mathbf{y} + \mathbf{z}) + t(\mathbf{z} + \mathbf{x}) = \mathbf{0}$, then $(r+t)\mathbf{x} + (r+s)\mathbf{y} + (s+t)\mathbf{z} = \mathbf{0}$. Since $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ is independent, this implies that r + t = 0, r+s = 0, and s+t = 0. The only solution is r = s = t = 0.
- d. No. In fact, $(\mathbf{x} + \mathbf{y}) (\mathbf{y} + \mathbf{z}) + (\mathbf{z} + \mathbf{w}) (\mathbf{w} + \mathbf{x}) = \mathbf{0}.$

Exercise 5.2.3 Find a basis and calculate the dimension of the following subspaces of \mathbb{R}^4 .

- a. span {(1, -1, 2, 0), (2, 3, 0, 3), (1, 9, -6, 6)}
- b. span {(2, 1, 0, -1), (-1, 1, 1, 1), (2, 7, 4, 1)}
- c. span {(-1, 2, 1, 0), (2, 0, 3, -1), (4, 4, 11, -3), (3, -2, 2, -1)}
- d. span {(-2, 0, 3, 1), (1, 2, -1, 0), (-2, 8, 5, 3), (-1, 2, 2, 1)}



Exercise 5.2.4 Find a basis and calculate the dimension of the following subspaces of \mathbb{R}^4 .

a.
$$U = \left\{ \begin{bmatrix} a \\ a+b \\ a-b \\ b \end{bmatrix} \middle| a \text{ and } b \text{ in } \mathbb{R} \right\}$$

b.
$$U = \left\{ \begin{bmatrix} a+b \\ a-b \\ b \\ a \end{bmatrix} \middle| a \text{ and } b \text{ in } \mathbb{R} \right\}$$

c.
$$U = \left\{ \begin{bmatrix} a \\ b \\ c+a \\ c \end{bmatrix} \middle| a, b, \text{ and } c \text{ in } \mathbb{R} \right\}$$

d. $U = \left\{ \begin{bmatrix} a-b \\ b+c \\ a \\ b+c \end{bmatrix} \middle| a, b, \text{ and } c \text{ in } \mathbb{R} \right\}$
e. $U = \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \middle| a+b-c+d=0 \text{ in } \mathbb{R} \right\}$
f. $U = \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \middle| a+b=c+d \text{ in } \mathbb{R} \right\}$

b.
$$\left\{ \begin{bmatrix} 1\\1\\0\\1 \end{bmatrix}, \begin{bmatrix} 1\\-1\\1\\0 \end{bmatrix} \right\}; \text{ dimension } 2.$$

d.
$$\left\{ \begin{bmatrix} 1\\0\\1\\0 \end{bmatrix}, \begin{bmatrix} -1\\1\\0\\1 \end{bmatrix}, \begin{bmatrix} 0\\1\\0\\1 \end{bmatrix} \right\}; \text{ dimension } 3.$$

f.
$$\left\{ \begin{bmatrix} -1\\1\\0\\0 \end{bmatrix}, \begin{bmatrix} 1\\0\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\0\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\0\\1\\0 \end{bmatrix} \right\}; \text{ dimension } 3.$$

Exercise 5.2.5 Suppose that $\{\mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{w}\}$ is a basis of \mathbb{R}^4 . Show that:

- a. { $\mathbf{x} + a\mathbf{w}$, \mathbf{y} , \mathbf{z} , \mathbf{w} } is also a basis of \mathbb{R}^4 for any choice of the scalar a.
- b. $\{\mathbf{x}+\mathbf{w}, \mathbf{y}+\mathbf{w}, \mathbf{z}+\mathbf{w}, \mathbf{w}\}$ is also a basis of \mathbb{R}^4 .
- c. { \mathbf{x} , $\mathbf{x} + \mathbf{y}$, $\mathbf{x} + \mathbf{y} + \mathbf{z}$, $\mathbf{x} + \mathbf{y} + \mathbf{z} + \mathbf{w}$ } is also a basis of \mathbb{R}^4 .

b. If $r(\mathbf{x} + \mathbf{w}) + s(\mathbf{y} + \mathbf{w}) + t(\mathbf{z} + \mathbf{w}) + u(\mathbf{w}) = \mathbf{0}$, then $r\mathbf{x} + s\mathbf{y} + t\mathbf{z} + (r+s+t+u)\mathbf{w} = \mathbf{0}$, so r = 0, s = 0, t = 0, and r+s+t+u = 0. The only solution is r = s = t = u = 0, so the set is independent. Since dim $\mathbb{R}^4 = 4$, the set is a basis by Theorem 5.2.7.

Exercise 5.2.6 Use Theorem 5.2.3 to determine if the following sets of vectors are a basis of the indicated space.

- a. $\{(3, -1), (2, 2)\}$ in \mathbb{R}^2
- b. $\{(1, 1, -1), (1, -1, 1), (0, 0, 1)\}$ in \mathbb{R}^3
- c. {(-1, 1, -1), (1, -1, 2), (0, 0, 1)} in \mathbb{R}^3
- d. {(5, 2, -1), (1, 0, 1), (3, -1, 0)} in \mathbb{R}^3
- e. {(2, 1, -1, 3), (1, 1, 0, 2), (0, 1, 0, -3), (-1, 2, 3, 1)} in \mathbb{R}^4
- f. {(1, 0, -2, 5), (4, 4, -3, 2), (0, 1, 0, -3), (1, 3, 3, -10)} in \mathbb{R}^4
- b. Yes
- d. Yes
- f. No.

Exercise 5.2.7 In each case show that the statement is true or give an example showing that it is false.

- a. If $\{\mathbf{x}, \mathbf{y}\}$ is independent, then $\{\mathbf{x}, \mathbf{y}, \mathbf{x}+\mathbf{y}\}$ is independent.
- b. If $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ is independent, then $\{\mathbf{y}, \mathbf{z}\}$ is independent.
- c. If $\{y, z\}$ is dependent, then $\{x, y, z\}$ is dependent for any x.
- d. If all of $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k$ are nonzero, then $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ is independent.
- e. If one of \mathbf{x}_1 , \mathbf{x}_2 , ..., \mathbf{x}_k is zero, then $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ is dependent.
- f. If $a\mathbf{x} + b\mathbf{y} + c\mathbf{z} = \mathbf{0}$, then $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ is independent.

- g. If $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ is independent, then $a\mathbf{x} + b\mathbf{y} + c\mathbf{z} = \mathbf{0}$ for some a, b, and c in \mathbb{R} .
- h. If $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\}$ is dependent, then $t_1\mathbf{x}_1 + t_2\mathbf{x}_2 + \dots + t_k\mathbf{x}_k = \mathbf{0}$ for some numbers t_i in \mathbb{R} not all zero.
- i. If $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\}$ is independent, then $t_1\mathbf{x}_1 + t_2\mathbf{x}_2 + \dots + t_k\mathbf{x}_k = \mathbf{0}$ for some t_i in \mathbb{R} .
- j. Every non-empty subset of a linearly independent set is again linearly independent.
- k. Every set containing a spanning set is again a spanning set.
- b. T. If $r\mathbf{y} + s\mathbf{z} = \mathbf{0}$, then $\mathbf{0}\mathbf{x} + r\mathbf{y} + s\mathbf{z} = \mathbf{0}$ so r = s = 0 because $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ is independent.
- d. F. If $\mathbf{x} \neq \mathbf{0}$, take k = 2, $\mathbf{x}_1 = \mathbf{x}$ and $\mathbf{x}_2 = -\mathbf{x}$.
- f. F. If $\mathbf{y} = -\mathbf{x}$ and $\mathbf{z} = \mathbf{0}$, then $1\mathbf{x} + 1\mathbf{y} + 1\mathbf{z} = \mathbf{0}$.
- h. T. This is a nontrivial, vanishing linear combination, so the \mathbf{x}_i cannot be independent.

Exercise 5.2.8 If *A* is an $n \times n$ matrix, show that det A = 0 if and only if some column of *A* is a linear combination of the other columns.

Exercise 5.2.9 Let $\{\mathbf{x}, \mathbf{y}, \mathbf{z}\}$ be a linearly independent set in \mathbb{R}^4 . Show that $\{\mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{e}_k\}$ is a basis of \mathbb{R}^4 for some \mathbf{e}_k in the standard basis $\{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_4\}$.

Exercise 5.2.10 If $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_6\}$ is an independent set of vectors, show that the subset $\{\mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_5\}$ is also independent.

If $r\mathbf{x}_2 + s\mathbf{x}_3 + t\mathbf{x}_5 = \mathbf{0}$ then $0\mathbf{x}_1 + r\mathbf{x}_2 + s\mathbf{x}_3 + 0\mathbf{x}_4 + t\mathbf{x}_5 + 0\mathbf{x}_6 = \mathbf{0}$ so r = s = t = 0.

Exercise 5.2.11 Let *A* be any $m \times n$ matrix, and let \mathbf{b}_1 , \mathbf{b}_2 , \mathbf{b}_3 , ..., \mathbf{b}_k be columns in \mathbb{R}^m such that the system $A\mathbf{x} = \mathbf{b}_i$ has a solution \mathbf{x}_i for each *i*. If $\{\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3, \ldots, \mathbf{b}_k\}$ is independent in \mathbb{R}^m , show that $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \ldots, \mathbf{x}_k\}$ is independent in \mathbb{R}^n .

Exercise 5.2.12 If $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_k\}$ is independent, show $\{\mathbf{x}_1, \mathbf{x}_1 + \mathbf{x}_2, \mathbf{x}_1 + \mathbf{x}_2 + \mathbf{x}_3, \dots, \mathbf{x}_1 + \mathbf{x}_2 + \dots + \mathbf{x}_k\}$ is also independent.

If $t_1\mathbf{x}_1 + t_2(\mathbf{x}_1 + \mathbf{x}_2) + \dots + t_k(\mathbf{x}_1 + \mathbf{x}_2 + \dots + \mathbf{x}_k) = \mathbf{0}$, then $(t_1 + t_2 + \dots + t_k)\mathbf{x}_1 + (t_2 + \dots + t_k)\mathbf{x}_2 + \dots + (t_{k-1} + t_k)\mathbf{x}_{k-1} + (t_k)\mathbf{x}_k = \mathbf{0}$. Hence all these coefficients are zero, so we obtain successively $t_k = 0$, $t_{k-1} = 0$, \dots , $t_2 = 0$, $t_1 = 0$.

Exercise 5.2.13 If $\{\mathbf{y}, \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_k\}$ is independent, show that $\{\mathbf{y}+\mathbf{x}_1, \mathbf{y}+\mathbf{x}_2, \mathbf{y}+\mathbf{x}_3, \dots, \mathbf{y}+\mathbf{x}_k\}$ is also independent.

Exercise 5.2.14 If $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k\}$ is independent in \mathbb{R}^n , and if \mathbf{y} is not in span $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k\}$, show that $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k, \mathbf{y}\}$ is independent.

Exercise 5.2.15 If A and B are matrices and the columns of AB are independent, show that the columns of B are independent.

Exercise 5.2.16 Suppose that $\{\mathbf{x}, \mathbf{y}\}$ is a basis of \mathbb{R}^2 , and let $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$.

- a. If A is invertible, show that $\{a\mathbf{x}+b\mathbf{y}, c\mathbf{x}+d\mathbf{y}\}$ is a basis of \mathbb{R}^2 .
- b. If $\{a\mathbf{x} + b\mathbf{y}, c\mathbf{x} + d\mathbf{y}\}$ is a basis of \mathbb{R}^2 , show that A is invertible.
- b. We show A^T is invertible (then A is invertible). Let $A^T \mathbf{x} = \mathbf{0}$ where $\mathbf{x} = [s \ t]^T$. This means as + ct = 0 and bs + dt = 0, so $s(a\mathbf{x} + b\mathbf{y}) + t(c\mathbf{x} + d\mathbf{y}) = (sa + tc)\mathbf{x} + (sb + td)\mathbf{y} = \mathbf{0}$. Hence s = t = 0 by hypothesis.

Exercise 5.2.17 Let A denote an $m \times n$ matrix.

- a. Show that $\operatorname{null} A = \operatorname{null} (UA)$ for every invertible $m \times m$ matrix U.
- b. Show that dim (null A) = dim (null (AV)) for every invertible $n \times n$ matrix V. [Hint: If $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ is a basis of null A, show that $\{V^{-1}\mathbf{x}_1, V^{-1}\mathbf{x}_2, \ldots, V^{-1}\mathbf{x}_k\}$ is a basis of null (AV).]

b. Each $V^{-1}\mathbf{x}_i$ is in $\operatorname{null}(AV)$ because $AV(V^{-1}\mathbf{x}_i) = A\mathbf{x}_i = \mathbf{0}$. The set

 $\{V^{-1}\mathbf{x}_1, \ldots, V^{-1}\mathbf{x}_k\}$ is independent as V^{-1} is invertible. If \mathbf{y} is in null (AV), then $V\mathbf{y}$ is in null (A) so let $V\mathbf{y} = t_1\mathbf{x}_1 + \cdots + t_k\mathbf{x}_k$ where each t_k is in \mathbb{R} . Thus $\mathbf{y} = t_1V^{-1}\mathbf{x}_1 + \cdots + t_kV^{-1}\mathbf{x}_k$ is in span $\{V^{-1}\mathbf{x}_1, \ldots, V^{-1}\mathbf{x}_k\}$.

Exercise 5.2.18 Let A denote an $m \times n$ matrix.

- a. Show that $\operatorname{im} A = \operatorname{im} (AV)$ for every invertible $n \times n$ matrix V.
- b. Show that dim (im A) = dim (im (UA)) for every invertible $m \times m$ matrix U. [Hint: If $\{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_k\}$ is a basis of im (UA), show

that $\{U^{-1}\mathbf{y}_1, U^{-1}\mathbf{y}_2, \dots, U^{-1}\mathbf{y}_k\}$ is a basis of im A.]

Exercise 5.2.19 Let U and W denote subspaces of \mathbb{R}^n , and assume that $U \subseteq W$. If dim U = n - 1, show that either W = U or $W = \mathbb{R}^n$.

Exercise 5.2.20 Let U and W denote subspaces of \mathbb{R}^n , and assume that $U \subseteq W$. If dim W = 1, show that either $U = \{0\}$ or U = W.

We have $\{0\} \subseteq U \subseteq W$ where dim $\{0\} = 0$ and dim W = 1. Hence dim U = 0 or dim U = 1 by Theorem 5.2.8, that is U = 0 or U = W, again by Theorem 5.2.8.