

# Design and Analysis of Algorithms

## *Flipped Class Offering*

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Course **Comp 582** (and Elec 420)

Time **1050AM to 1205PM**

Location **DCH 1055**

**Part II: Algorithmic Foundations of Data Science**



# Pre-requisite Linear Algebra

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## Source:

These slides are based on source material (including notation, concepts, and presentation approach) from *Basic Vector Space Methods in Signal and Systems Theory* By C. Sidney Burrus (Rice University, Houston, Texas, USA)

Acknowledgement: We thank Ashutosh Ingole (IIT Madras) for collaboration that resulted in these slides.

# Topics in this Lecture

1. Set Theory
2. Vectors and vector spaces
  - 2.a Vectors, Vector Space and Subspace
  - 2.b Basis and Dimension of a Vector Space
  - 2.c Change of Basis
3. A Matrix Times a Vector
  - 3.a Introducing the Role of Matrices
  - 3.b Dual Basis and Orthogonal Basis
4. General Solutions of Simultaneous Equations



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# Set Theory

# Set Theory

- A *set* is a collection of *distinct objects*.
  - Example: Set  $A = \{1, 2, 3, 4\}$ .
- A *finite set* has a finite number of objects.
  - Set  $A$  in the above example is a finite set.
- An *infinite set* is a set that has an infinite number of objects.
  - Example:  $\mathbb{Z} = \{\dots - 2, -1, 0, 1, 2 \dots\}$  is the set of all integers.
  - Similarly,  $\mathbb{R}$  and  $\mathbb{C}$  are the sets of real and complex numbers, respectively.

# Set Theory (contd.)

- ▶ A set  $A$  is a *subset* of a set  $B$ , if all elements of  $A$  are also elements of  $B$ .
  - ▶ It is denoted by  $A \subseteq B$ .
  - ▶ An empty set is always a subset of every set.
- ▶ The *power set* of a set  $S$  is the set of all subsets of  $S$ .
  - ▶ It is denoted by  $2^S$ .
  - ▶ Example: If  $S = \{1,2,3\}$ , then
$$2^S = \{\{\}, \{1\}, \{2\}, \{3\}, \{1,2\}, \{1,3\}, \{2,3\}, \{1,2,3\}\}.$$



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# Vectors and Vector Spaces

# Vectors

- A vector is a mathematical structure that has the ability to represent both *magnitude* and *direction* simultaneously.
- A point  $(x, y)$  on a Cartesian coordinate plane is an example of a vector.
- A *vector of dimension  $n$*  is an *ordered* collection of  $n$  elements called *components* or *entries*.
  - Components can be real or complex numbers.
- A *scalar* is a dimensionless quantity.
  - For example, one that can be described by a single real number.



# A Signal as a Vector

- Information about many real world phenomena (audio, video, radar, etc.) are conveyed as signals
  - Typically patterns that repeat overtime represented as periodic functions.
- One period of the signal can be represented as a vector

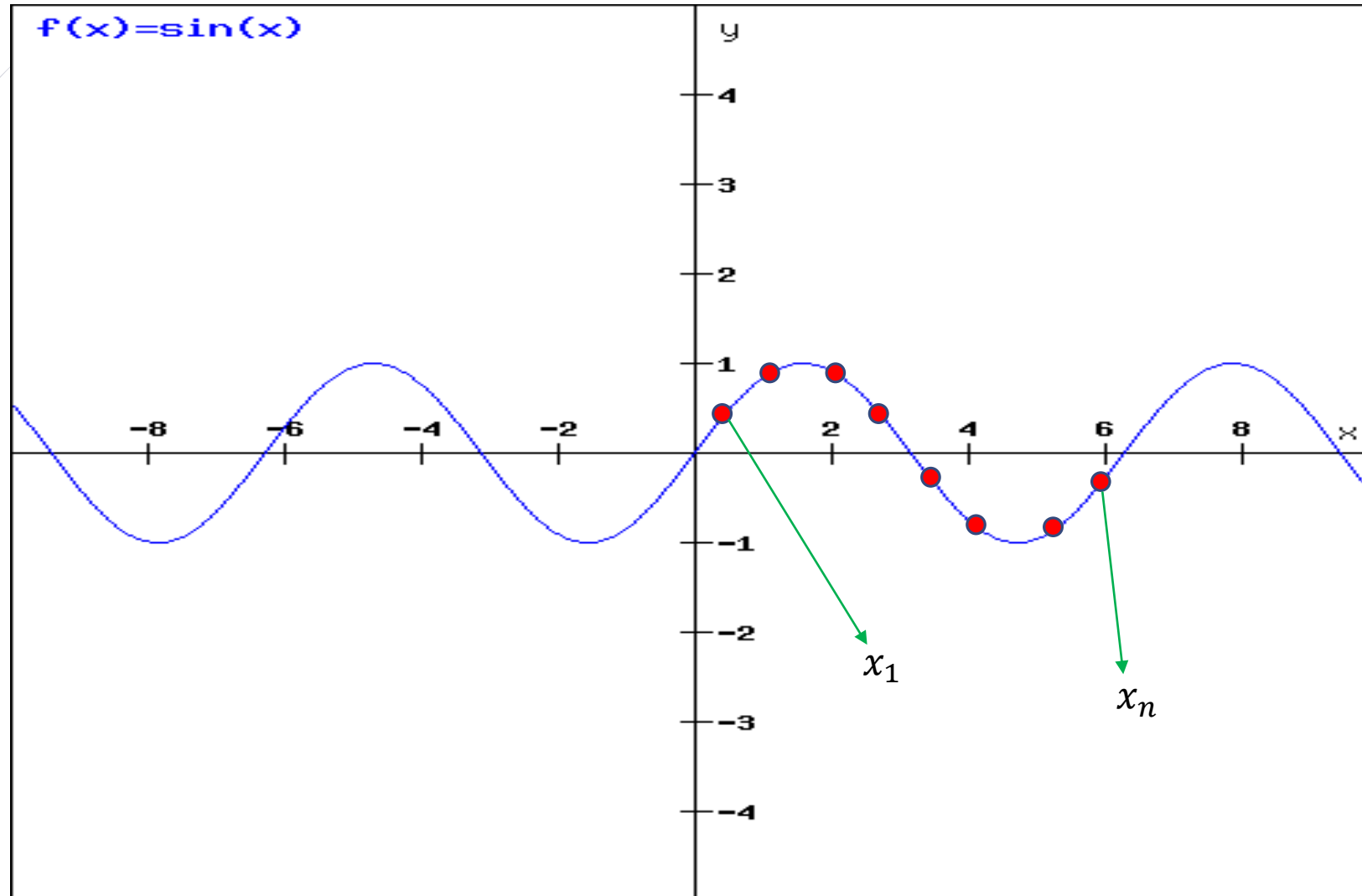
$$\mathbf{x} = (x_1, x_2, \dots, x_t, \dots, x_n)$$

Where  $x_1$  is the sample representing the beginning of the period,  $x_n$  is the sample representing the end. All other  $x_i$ ,  $2 \leq i < n$ , represent intermediate samples.

- This perspective will serve as a running example.

# A Signal as a Vector

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# Vector Operations Leading to Vectors

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- *Vector Addition:* For two vectors  $\mathbf{a} = (a_1, a_2, \dots, a_n)$  and  $\mathbf{b} = (b_1, b_2, \dots, b_n)$ , the vector sum is given by
$$\mathbf{a} + \mathbf{b} = (a_1 + b_1, a_2 + b_2, \dots, a_n + b_n).$$
- *Scalar Multiplication:* Let  $\ell$  be a scalar. The scalar multiplication is given by  $\ell \mathbf{a} = (\ell a_1, \ell a_2 \cdots \ell a_n)$ .
- *Linear Combination:* When  $\ell_1$  and  $\ell_2$  are two scalars,  $\ell_1 \mathbf{a} + \ell_2 \mathbf{b}$  is called a *linear combination* of  $\mathbf{a}$  and  $\mathbf{b}$ .
- *Span:* Let  $\mathbf{X}$  be a set of vectors. The set of all linear combinations of vectors of  $\mathbf{X}$  is called the span of  $\mathbf{X}$ .
  - *Notice: the span leads to a whole “space” of vectors!*

# Vector Operations Resulting in Scalars

- ▶ An *Inner Product* of two vectors denoted by  $\langle \mathbf{a}, \mathbf{b} \rangle$  is any notion of multiplication of  $\mathbf{a}$  and  $\mathbf{b}$  resulting in a scalar and obeys the following rules.
- ▶ Given the vectors  $\mathbf{a}$ ,  $\mathbf{b}$  and  $\mathbf{c}$ 
  1. Commutative, i.e.,  $\langle \mathbf{a}, \mathbf{b} \rangle = \langle \mathbf{b}, \mathbf{a} \rangle$ ,
  2. Distributive, i.e.,  $\langle \mathbf{a}, \mathbf{b} + \mathbf{c} \rangle = \langle \mathbf{a}, \mathbf{b} \rangle + \langle \mathbf{a}, \mathbf{c} \rangle$ .
  3. Positive-Definite, i.e.,  $\langle \mathbf{a}, \mathbf{a} \rangle \geq 0$  with equality iff  $\mathbf{a} = \mathbf{0}$ , and
  4. For any scalar  $\ell$ ,  $\langle \ell \mathbf{a}, \mathbf{b} \rangle = \ell \langle \mathbf{a}, \mathbf{b} \rangle$ .
- ▶ The *Dot Product* is the most common inner product. Consider  $\mathbf{a} = (a_1, a_2, \dots, a_n)$  and  $\mathbf{b} = (b_1, b_2, \dots, b_n)$  then the dot product is given by

$$\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + \dots + a_n b_n.$$

# Vector Space

- ▶ A vector space  $\mathbf{V}$  is a set of vectors that is closed under finite vector addition and scalar multiplication, that satisfy the following eight conditions.
  - ▶ Example:  $n$ -dimensional Euclidean space  $\mathbb{R}^n$ .
  - ▶ In  $\mathbb{R}^n$ , every element is represented by a set of  $n$  real numbers which is a vector in  $\mathbb{R}^n$ .
  - ▶ Closure: Given any two vectors  $\mathbf{a}$  and  $\mathbf{b}$ ,  $\mathbf{a} + \mathbf{b}$  is also in  $\mathbb{R}^n$ .
- ▶ In order for  $\mathbf{V}$  to be a vector space, the following properties must hold for all vectors  $\mathbf{u}, \mathbf{v}, \mathbf{w} \in \mathbf{V}$  and any scalars  $\alpha, \beta$ .
  1. Commutativity:
$$\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}.$$
  2. Associativity of vector addition:
$$(\mathbf{u} + \mathbf{v}) + \mathbf{w} = \mathbf{u} + (\mathbf{v} + \mathbf{w}).$$

# Vector Space (contd.)

3. Additive identity:  $\exists \mathbf{0} \in V$  s.t.  $\forall \mathbf{u} \in V$   
 $\mathbf{0} + \mathbf{u} = \mathbf{u} + \mathbf{0} = \mathbf{u}.$

4. Additive inverse:  $\forall \mathbf{u} \in V, \exists -\mathbf{u} \in V$  s.t.  
 $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}.$

5. Associativity of scalar multiplication:  
 $\alpha(\beta\mathbf{u}) = (\alpha\beta)\mathbf{u}.$

6. Distributivity of scalar sums:  
 $(\alpha + \beta)\mathbf{u} = \alpha\mathbf{u} + \beta\mathbf{u}.$

7. Distributivity of vector sums:  
 $\alpha(\mathbf{u} + \mathbf{v}) = \alpha\mathbf{u} + \alpha\mathbf{v}.$

8. Scalar multiplication identity:  
 $1\mathbf{u} = \mathbf{u}.$

“**0**” is a zero vector or null vector having magnitude equal to zero, and thus has all components equal to zero.

This additive inverse of **u** denoted by “**-u**” has the same components as **u**, but negated.

# Linear Dependence and Independence of Vectors

- ▶ A set of vectors is said to *linearly dependent* iff one of the vectors in the set can be written as a linear combination of the other vectors.
- ▶ Whenever no vector in the set can be written as a linear combination of rest of the vectors in the set, then the vectors are said to be *linearly independent*.
- ▶ Exercise: Prove that  $\mathbf{u}, \mathbf{v}, \mathbf{w}$  are linearly dependent and  $\mathbf{u}, \mathbf{v}$  are linearly independent.  
$$\mathbf{u} = (1, 1), \quad \mathbf{v} = (-3, 2), \quad \mathbf{w} = (2, 4).$$

# Subspace of a Vector Space

- ▶ Let  $V$  be a vector space. Then  $W \subseteq V$  is a *subspace* of  $V$  if  $W$  is itself a vector space.
- ▶ Example: Consider a simple vector space  $\mathbb{R}^3$ , which is the 3-dimensional Euclidean space. Its subspaces are
  - ▶ The origin,
  - ▶ Any line passing through the origin,
  - ▶ Any plane passing through the origin, and finally
  - ▶  $\mathbb{R}^3$ .
- ▶ Exercise: Would the unit cube centered at the origin be a subspace? In particular, would it be closed?



# Basis and Dimension of a Vector Space

- ▶ A *basis* of a vector space  $V$  is defined as a subset of vectors in  $V$  that are linearly independent and span  $V$ .
- ▶ These are called *basis vectors*.
- ▶ A vector space  $V$  can have many different bases, but there are always the same number of basis vectors in each of them.
- ▶ The number of basis vectors in a basis of  $V$  is the *dimension* of  $V$ .
- ▶ Example: In  $\mathbb{R}^2$ ,  $\mathbf{u} = (1,0)$  and  $\mathbf{v} = (0,1)$  forms a basis. Any vector  $\mathbf{w} = (a,b)$  can be uniquely written as the linear combination  $\mathbf{w} = a\mathbf{u} + b\mathbf{v}$ . Its dimension is 2.

# Standard Basis

- In a *standard basis*, each basis vector has only one nonzero entry whose magnitude is 1.
- Example: In the real vector space  $\mathbb{R}^3$ , the standard basis is the set of vectors  $\{(1,0,0), (0,1,0), (0,0,1)\}$ .
- On the other hand, vectors  $(3, 2)$  and  $(2, 1)$  are also a basis for  $\mathbb{R}^2$  but not a standard basis.
  - This means any vector in  $\mathbb{R}^2$  can be generated as a linear combination of vectors  $(3, 2)$  and  $(2, 1)$  but it is not a standard basis for obvious reasons.

# Change of Basis

- ▶ We know that there are many different bases other than standard basis.
  - ▶ It is often convenient to work with more than one basis for a vector space.
- ▶ Let  $V$  be a vector space and let  $S = \{v_1 \cdots v_n\}$  be a set of vectors which forms a basis for  $V$ .
  - ▶ If  $S$  is a basis for  $V$ , then every vector  $v \in V$  can be expressed as:
$$v = c_1 v_1 + c_2 v_2 + \cdots + c_n v_n.$$
  - ▶ Think of  $(c_1, c_2, \dots, c_n)$  as the coordinates of  $v$  relative to the basis  $S$ .
    - ▶ These coordinates are easily understood if we choose the standard basis of course.
  - ▶ Let  $(c'_1, c'_2, \dots, c'_n)$  be the coordinates of  $v$  relative to some other basis  $S'$ .
    - ▶ This process of transformation of coordinates from one basis to another is called *change of basis*.

# Change of Basis: A Simple Example

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►  $B = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$  and  $B' = \left\{ \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \begin{bmatrix} -2 \\ 1 \end{bmatrix} \right\}$

► Two different bases in  $\mathbb{R}^2$ .

► The Change of basis from  $B'$  to  $B$  can be represented as a matrix

$$A = \begin{bmatrix} 3 & -2 \\ 1 & 1 \end{bmatrix}.$$

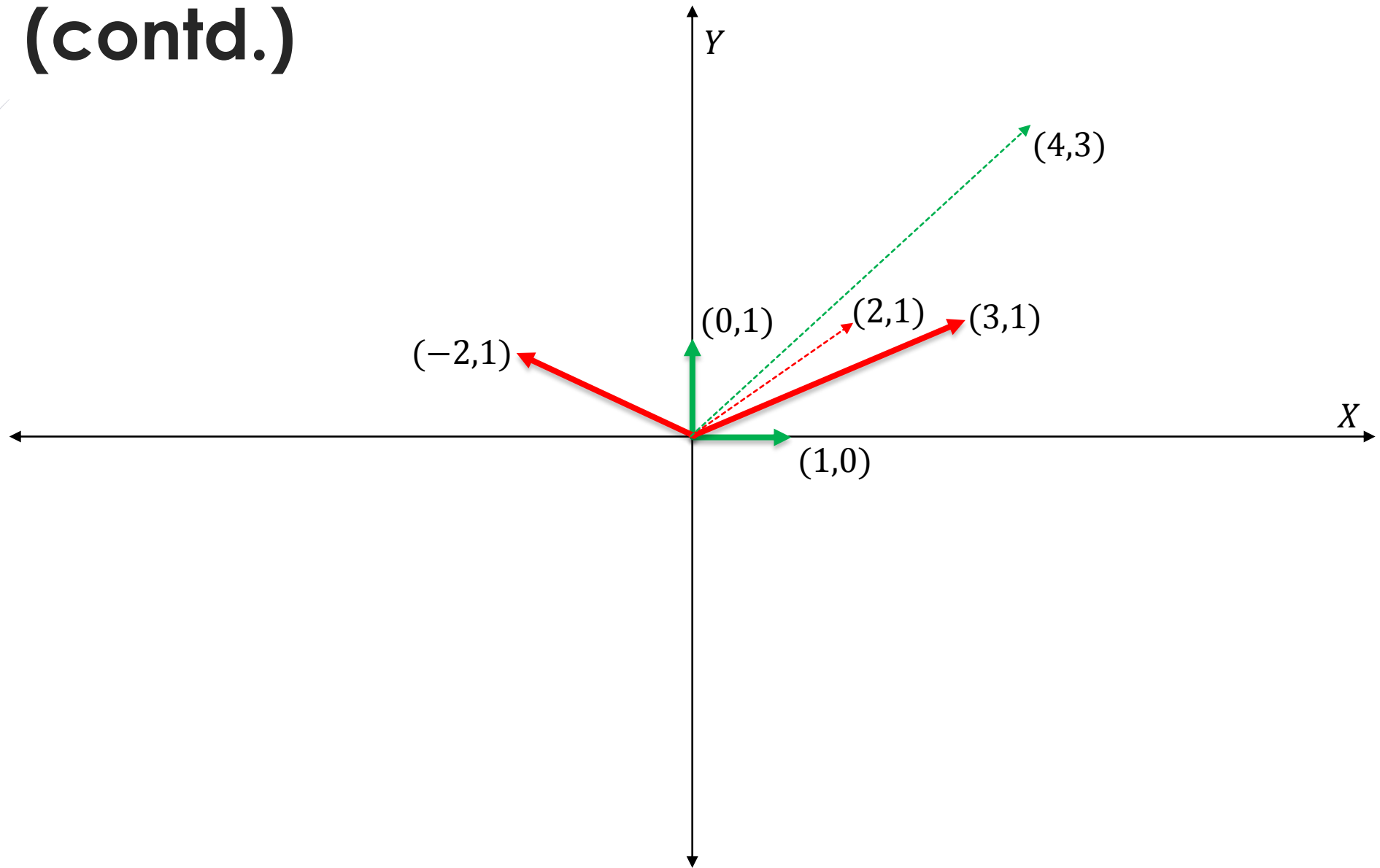
► Suppose the coordinates of vector  $\mathbf{v} \in \mathbb{R}^2$  relative to the basis  $B'$  are  $[\mathbf{v}]_{B'} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ .

► The coordinates of vector  $\mathbf{v} \in \mathbb{R}^2$  relative to basis  $B$  are

$$[\mathbf{v}]_B = \begin{bmatrix} 3 & -2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 3 \end{bmatrix}.$$

► Notice that change of basis is a transformation which requires multiplication of a matrix and a vector.

# Change of Basis: A Simple Example (contd.)



# A Matrix Times a Vector

# Introducing the Role of Matrices to Change the Basis

$$Ax = b \quad \dots (1)$$

is a simple matrix equation, where  $x$  and  $b$  are vectors from the same or perhaps different vector spaces and  $A$  is a matrix.

- ▶ This equation has variety of special cases.
  - ▶ The matrix  $A$  may be square or may be rectangular
  - ▶ be symmetric
  - ▶ orthogonal
  - ▶ or have some of many other characteristics which would be interesting.
  - ▶ The entries in  $A$  could be complex for some important applications.
- ▶ Obvious observation: Given any two elements of *eq. (1)* we can find the third element if a solution exists.
- ▶ We will focus on finite dimensions.

# Dual Basis contd.

- Inverse of a square matrix  $A$  is denoted by  $A^{-1}$  and it is defined as
  - Remember,  $AA^{-1} = I$  where  $I$  is a unit matrix.
- The rows of matrix  $A^{-1}$  is defined to be the *dual basis* (of our original basis) for  $\mathbf{V}$ .
  - Exists only if  $A$  is a square matrix.
- Example : Let  $A = \begin{bmatrix} 3 & -2 \\ 1 & 1 \end{bmatrix}$  then the inverse of  $A$  is
$$A^{-1} = \frac{1}{5} \begin{bmatrix} 1 & 2 \\ -1 & 3 \end{bmatrix} = \begin{bmatrix} 1/5 & 2/5 \\ -1/5 & 3/5 \end{bmatrix}$$
(Use determinant x adjugate)



# Introduction to $Ax = b$ (contd.)

- In *eq. (1)*, if we take the vectors (i.e.  $x$  and  $b$ ) and the matrix  $A$ .
  - Following our earlier example the product  $Ax$  can be interpreted as a change of basis.
- The vector stays the same but its basis changes.

# Introduction to $A\mathbf{x} = \mathbf{b}$ (contd.)

- ▶ Continuing with our view of matrix multiplication as a change of basis:
  - ▶ The operation  $A\mathbf{x} = \mathbf{b}$  can now be viewed as  $\mathbf{x}$  being a set of weights so that  $\mathbf{b}$  is a weighted sum of the columns of  $A$ .

This view is shown below. If the vector  $\mathbf{a}_i$  is the  $i^{th}$  column of  $A$ , the product takes the form

$$A\mathbf{x} = x_1 \begin{bmatrix} \vdots \\ \mathbf{a}_1 \\ \vdots \end{bmatrix} + x_2 \begin{bmatrix} \vdots \\ \mathbf{a}_2 \\ \vdots \end{bmatrix} + \cdots + x_n \begin{bmatrix} \vdots \\ \mathbf{a}_n \\ \vdots \end{bmatrix} = \mathbf{b}$$

In other words,  $\mathbf{b}$  will lie in the space spanned by the columns of  $A$  at a location determined by  $\mathbf{x}$ .

# A Basis and *Dual* Basis

- Recall that, a set of linearly independent vectors  $x_n$  forms a basis for a vector space  $\mathbf{V}$  if every vector  $\mathbf{x}$  in the space can be uniquely written as

$$\mathbf{x} = \sum_n a_n x_n \quad \cdots (2)$$

- We also know that a basis can be represented as a matrix where the  $i^{th}$  column of that matrix is the an individual basis from the set.
  - As before, let  $A$  be that matrix of basis vectors.

# Dual Basis contd.

- Recall that, column vectors of matrix  $A$  in previous slide forms a basis in  $\mathbb{R}^2$ .
- Let us give the same name to this basis as before namely  $\mathbf{B}'$ .
  - $\mathbf{B}' = \left\{ \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \begin{bmatrix} -2 \\ 1 \end{bmatrix} \right\}$ .
- Let  $\mathbf{B}''$  be the dual basis of  $\mathbf{B}'$  and from the determined by taking the inverse of  $\mathbf{B}'$ 
  - Exercise: Verify that  $\mathbf{B}'' = \left\{ \begin{bmatrix} 1/5 \\ 2/5 \end{bmatrix}, \begin{bmatrix} -1/5 \\ 3/5 \end{bmatrix} \right\}$ .

# Orthogonal and Orthonormal Basis

► **Orthogonal:** Two vectors are said to be orthogonal if their dot product is zero.

► Example:  $\begin{bmatrix} 1 \\ \sqrt{2} \\ 1 \end{bmatrix}$  and  $\begin{bmatrix} 1 \\ -\sqrt{2} \\ 1 \end{bmatrix}$  are orthogonal vectors.

►  $\begin{bmatrix} 1 \\ \sqrt{2} \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ -\sqrt{2} \\ 1 \end{bmatrix} = (1 \times 1) + (\sqrt{2} \times -\sqrt{2}) + (1 \times 1) = 1 - 2 + 1 = 0$

► **Orthonormal:** If the two orthogonal vectors are unit vectors then they are called orthonormal vectors.

► Example:  $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$  and  $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$  are unit vectors and their dot product is zero and hence they are orthonormal vectors.

# Orthogonal Basis Observation

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- ▶ A given basis is called an orthogonal basis if the basis vectors are mutually (pair-wise) orthogonal.
- ▶ Given any two vectors from an orthogonal basis, their dot product is zero, i.e. they are orthogonal vectors.

# Orthonormal Basis Observations

- ▶ When the vectors of an orthogonal basis are unit vectors the resulting basis is an orthonormal basis.
- ▶ Example: The set of vectors  $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$  forms an orthonormal basis of  $\mathbb{R}^3$ .

# Orthonormal Basis Observations (contd.)

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- ▶ Example: Let  $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$  where the column vectors of  $A$  forms an orthonormal basis in  $\mathbb{R}^2$ .
- ▶ Let this basis is denoted by  $\mathbf{B} = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$
- ▶ Here,  $A^{-1} = A^T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$  and
- ▶ The row vectors of  $A^{-1}$  forms a dual basis and let this dual basis is denoted by  $\mathbf{B}' = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$ .
- ▶ From above example, we note that that orthonormal basis  $\mathbf{B}$  is it's own dual.