

# **CS 6351 DATA COMPRESSION**

## **THIS LECTURE: TRANSFORMS PART II**

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# OBJECTIVES OF THIS LECTURE

By the end of this lecture, you will be able to:

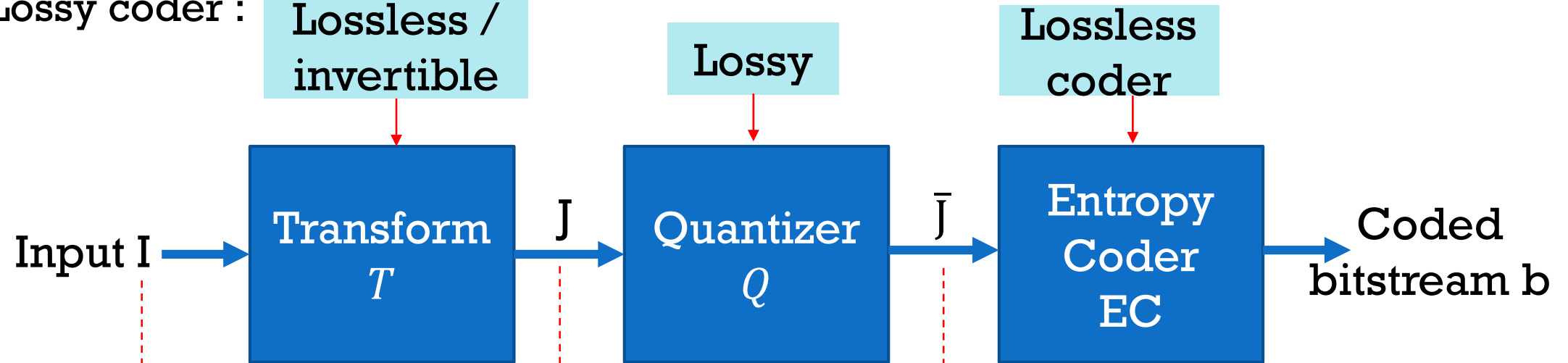
- Describe vector spaces, and related concepts such as linear independence, linear combinations, bases (axes), and dimensionality of vector spaces
- Draw connections between vectors and digital audio/visual signals, and also between vectors and analog signals
- Explain and appreciate the connections b/w vector space concepts and relevant audio/visual concepts
- Tie matrix-column multiplication with expressing vectors as linear combinations of basis vectors
- Prove that transforms are but a change of bases, a change of coordinate systems
- Explicate the connection between transforms, bases, human senses, and the kind of basis conducive to effective lossy compression

# OUTLINE

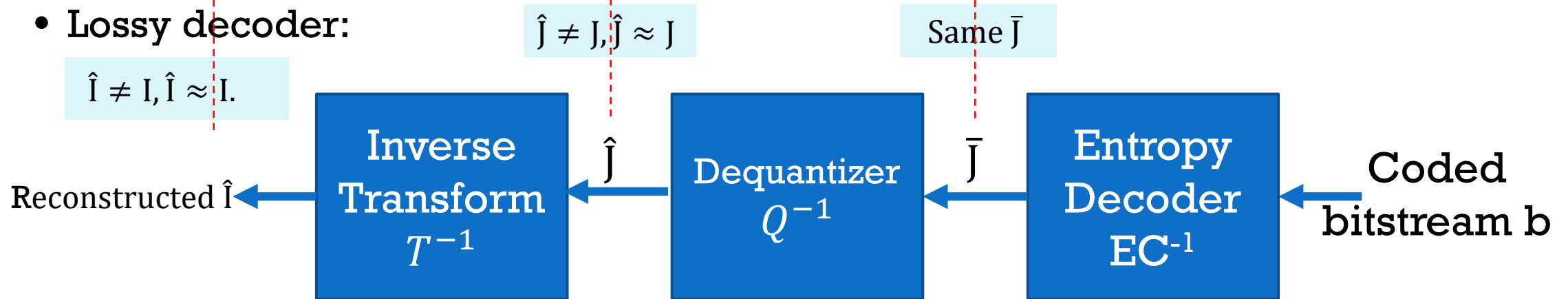
- Vector spaces
- Vector space perspective of transforms
- Connection between
  - transforms,
  - Vector space bases,
  - human senses, and
  - the kind of basis conducive to effective lossy compression

# RECALL: GENERAL SCHEME OF LOSSY COMPRESSION

- Lossy coder :



- Lossy decoder:



The entire data loss is limited to the quantizer

4

# VECTOR SPACES OVER $\mathbb{R}$

## -- PRELIMINARIES (1/2) --

- A vector space  $V$  is a set of objects (called *vectors*) with two operations:
    - Vector addition (+): for all  $u, v \in V$ , the sum  $u + v$  is a new vector in  $V$
    - Scalar multiplication (.) of a number by a vector: for all  $a \in \mathbb{R}$  and  $u \in V$ , the product  $a.u$  (typically written  $au$ ) is a new vector in  $V$
- such that certain properties (called *axioms*) are satisfied (to be seen)
- It is a generalization of 2D /3D vectors you studied in Physics, and how to add/subtract them, and extend/shrink them by multiplying them by a real number

# VECTOR SPACES OVER $\mathbb{R}$

## -- PRELIMINARIES (2/2) --

- One big take-away for data compression is the notion of **basis** of vector space
  - A basis is a generalization of axes (like x-y axes and x-y-z axes)
  - There is a special connection between transforms and bases
  - Interest: a basis that “aligns” with the human eyes/ears

# DEFINITION OF A VECTOR SPACE OVER $\mathbb{R}$

## -- FORMAL DEFINITION--

A vector space  $(V, +, \cdot, 0)$  is a non-empty set  $V$  with two operation  $(+)$  and  $(\cdot)$  in  $V$  that satisfy the following properties (called axioms):

1.  $\forall u, v \in V, u + v = v + u$  (Commutativity, i.e.,  $+$  is commutative)
2.  $\forall u, v, w \in V, (u + v) + w = u + (v + w)$  (Associativity, i.e.,  $+$  is associative)
3.  $\exists 0 \in V$  such that  $\forall u \in V, u + 0 = 0 + u = u$  ( $0$  is called the *zero vector*)
4.  $\forall u \in V, \exists v \in V$  such that  $u + v = v + u = 0$ ;  $v$  is called the *opposite vector* of  $u$  and is denoted  $-u$  (so  $u + (-u) = (-u) + u = 0$ )
5.  $\forall a \in \mathbb{R}$  and  $\forall u, v \in V, a(u + v) = au + av$
6.  $\forall a, b \in \mathbb{R}$  and  $\forall u \in V, (a + b)u = au + bu$
7.  $\forall a, b \in \mathbb{R}$  and  $\forall u \in V, a(bu) = (ab)u$
8.  $\forall u \in V, 0u = 0, \text{ and } 1u = u$

# VECTOR SPACE EXAMPLES (1/4)

- Take  $V = \mathbb{R} \times \mathbb{R} = \{(x, y) | x \in \mathbb{R} \text{ and } y \in \mathbb{R}\}$ , that is, every vector  $u$  is of the form  $(x, y)$ , where
  - $(x, y) + (x', y') \stackrel{\text{def}}{=} (x + x', y + y')$  (note:  $\stackrel{\text{def}}{=}$  means “by definition”)
  - $a(x, y) \stackrel{\text{def}}{=} (ax, ay)$
  - $0 \stackrel{\text{def}}{=} (0, 0)$
- You can easily verify that the 8 axioms are satisfied, for example
  - $(x, y) + (x', y') = (x', y') + (x, y)$  because  $(x + x', y + y') = (x' + x, y' + y)$
  - $0 + (x, y) = (x, y)$  because  $0 + (x, y) = (0, 0) + (x, y) = (0 + x, 0 + y) = (x, y)$
  - $(x, y) + (-x, -y) = (x - x, y - y) = (0, 0) = 0$
  - $\forall a, b \in \mathbb{R} \text{ and } \forall (x, y) \in V$ , we have  $(a + b)(x, y) = ((a + b)x, (a + b)y) = (ax + bx, ay + by) = (ax, ay) + (bx, by) = a(x, y) + b(x, y)$ , therefore  $(a + b)(x, y) = a(x, y) + b(x, y)$
  - $0 \cdot (x, y) = 0$  because  $0 \cdot (x, y) = (0 \cdot x, 0 \cdot y) = (0, 0) = 0$
  - $1 \cdot (x, y) = (x, y)$  because  $1 \cdot (x, y) = (1 \cdot x, 1 \cdot y) = (x, y)$



# VECTOR SPACE EXAMPLES (2/4)

## -- VISUAL/GRAPHICAL REPRESENTATIONS --

- Draw x-y axes: each point has two coordinates. Origin= $(0,0)=0$

- $u = (2,1)$ ,  $v = (1,3)$

- Vector  $(2,1)$ : arrow from point  $(0,0)$  to point  $(2,1)$

- $u + v = (3,4)$ , visually:

- Make a “copy” of  $v$  starting from the tip of  $u$
  - Take arrow from  $(0,0)$  to the tip of copy of  $v$

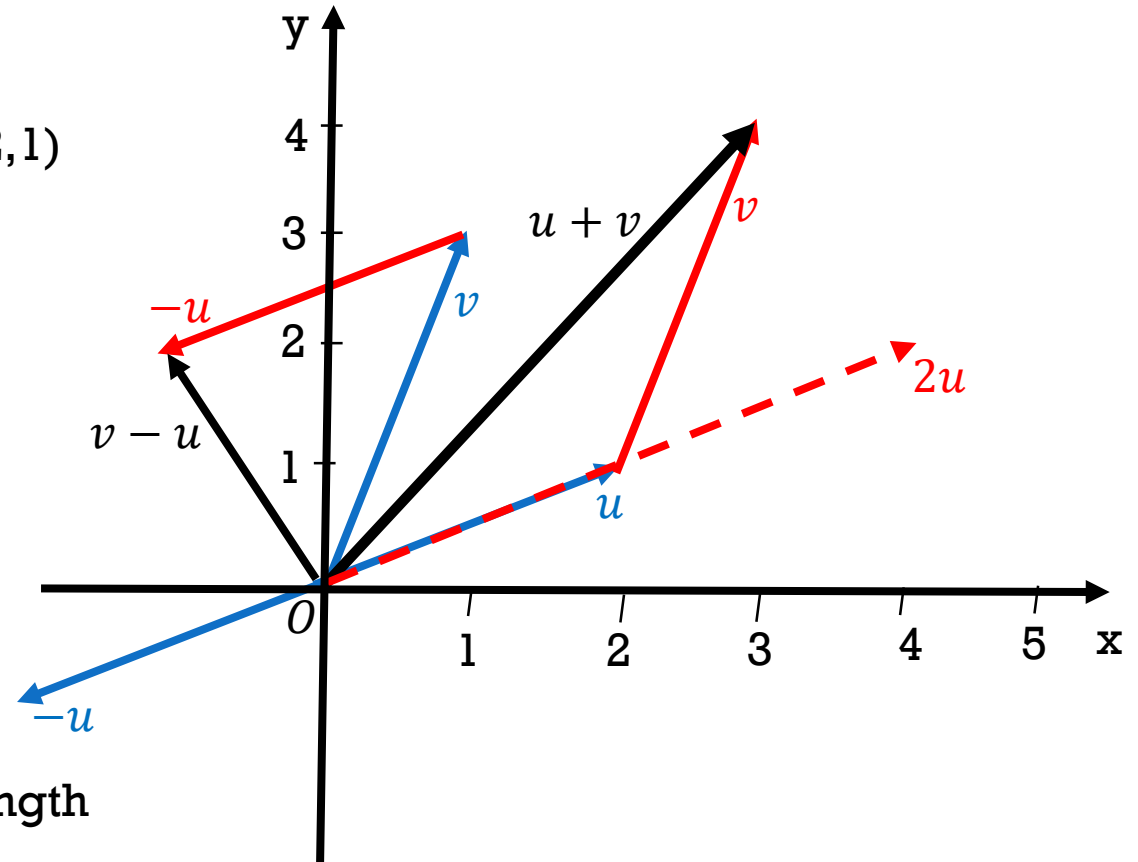
- $-u = (-2,-1)$ , visually:

- Take reflection of  $u$  from the origin

- $2u = (4,2)$ , visually:

- Same angle and orientation as  $u$ , twice the length

- $v - u = (-1,2)$ , same as  $v + (-u)$



# VECTOR SPACE EXAMPLES (3/4)

- Take  $V = \mathbb{R} \times \mathbb{R} \times \mathbb{R} = \{(x, y, z) | x \in \mathbb{R}, y \in \mathbb{R} \text{ and } z \in \mathbb{R}\}$ , that is, every vector  $u$  is of the form  $(x, y, z)$ , where
  - $(x, y, z) + (x', y', z') \stackrel{\text{def}}{=} (x + x', y + y', z + z')$
  - $a(x, y, z) \stackrel{\text{def}}{=} (ax, ay, az)$
  - $0 \stackrel{\text{def}}{=} (0, 0, 0)$
- You can easily verify that the 8 axioms are satisfied
- Note: We typically denote
  - $\mathbb{R} \times \mathbb{R} = \mathbb{R}^2$  // set of couples or pairs of real numbers
  - $\mathbb{R} \times \mathbb{R} \times \mathbb{R} = \mathbb{R}^3$  // set of triples
  - $\underbrace{\mathbb{R} \times \mathbb{R} \times \dots \times \mathbb{R}}_{n \text{ times}} = \mathbb{R}^n$  // set of  $n$ -tuples of the form  $(x_1, x_2, \dots, x_n)$  where every  $x_i \in \mathbb{R}$

# VECTOR SPACE EXAMPLES (4/4)

- Take  $V = \mathbb{R}^n = \{(x_1, x_2, \dots, x_n) | x_i \in \mathbb{R} \text{ for all } i = 1, 2, \dots, n\}$ , that is, every vector  $u$  is of the form  $(x_1, x_2, \dots, x_n)$ , where
  - $(x_1, x_2, \dots, x_n) + (y_1, y_2, \dots, y_n) \stackrel{\text{def}}{=} (x_1 + y_1, x_2 + y_2, \dots, x_n + y_n)$
  - $a(x_1, x_2, \dots, x_n) \stackrel{\text{def}}{=} (ax_1, ax_2, \dots, ax_n)$
  - $0 \stackrel{\text{def}}{=} (0, 0, \dots, 0)$
- You can easily verify that the 8 axioms are satisfied

# SOUND SIGNALS AS “VECTORS”

- A digital audio signal, e.g., a sound recording, is a sequence of sound samples, i.e., a sequence of real numbers  $x_1, x_2, \dots, x_n$
- Each such signal can be viewed as a vector  $(x_1, x_2, \dots, x_n)$  in  $\mathbb{R}^n$
- **Adding two sound signals**  $(x_1, x_2, \dots, x_n)$  and  $(y_1, y_2, \dots, y_n)$  into  $(x_1, x_2, \dots, x_n) + (y_1, y_2, \dots, y_n) \stackrel{\text{def}}{=} (x_1 + y_1, x_2 + y_2, \dots, x_n + y_n)$  is like **playing the two sound recordings at the same time**
- **Multiplying a sound signal**  $(x_1, x_2, \dots, x_n)$  by some number  $a$  (e.g.,  $a=3$ ) to get  $a(x_1, x_2, \dots, x_n) \stackrel{\text{def}}{=} (ax_1, ax_2, \dots, ax_n)$  is like playing the sound 3 times louder, i.e., **raising the volume**
  - **If  $0 < a < 1$** , as for example  $a = \frac{1}{2}$ , is like **reducing the volume** (e.g., making the sound less loud)

# IMAGES AS “VECTORS”

- A digital image  $I$  of  $n$  rows and  $m$  columns can be viewed as a vector in  $\mathbb{R}^{n \times m}$ 
  - Like stacking the rows one after another, or
  - Stacking the columns one on top of the other
- **Adding two vectors** is like **superposing the two images** on top of each other
- **Multiplying a vector** by some number  $a$  (e.g.,  $a=3$  or  $a = \frac{1}{2}$ ) is like **making the colors (or gray shades) proportionally darker or lighter**
- The **opposite**  $-I$  is what we typically call the **negative of an image/photo**

# CAN ANALOG SIGNALS BE VIEWED AS VECTORS?

- We just saw that digital signals (whether audio or visual) can be viewed as vectors
- How about analog signals (like those captured by old recorders or old cameras)?
  - Can you view them as vectors in a vector space?
  - If so, what would an analog signal correspond to mathematically?
- Why should we care, since analog technology is old, obsolete, and deprecated?
  - Also, even if some preserved old recordings/photos are still of interest, they can be digitized, so why bother with analog signals as vectors?
- Answer: Analysis of analog signals is like analysis of continuous functions, which is easier and more insightful, in some respects, than discrete functions
  - Using Calculus and Mathematical Analysis

# ANALOG AUDIO SIGNALS AS VECTORS

- Take  $V$  as the set of all functions  $f(t)$  of one real variable  $t$  ( $t$  is like time)
- View each such function  $f$  as an (abstract) vector
- Addition of two vectors is addition of two functions:  $f + g$  is such that
  - $(f + g)(t) \stackrel{\text{def}}{=} f(t) + g(t)$
  - Example: like playing two analog sounds simultaneously
- Multiplying a vector (i.e., a function  $f$ ) by a number  $a$  gives us a new vector (or function)  $af$  where  $(af)(t) \stackrel{\text{def}}{=} a \cdot f(t)$ 
  - Example: like making the volume of an analog (old) radio louder or quieter
- The zero vector (or function)  $0$  is the zero function  $f$  where  $f(t) = 0 \forall t$ 
  - The zero function is the equivalent of “dead silence”
- The opposite vector (or function) of  $f$  is  $-f$  where  $(-f)(t) \stackrel{\text{def}}{=} -f(t)$
- One can show that this  $(V, +, \cdot, 0)$  is a vector space, i.e., satisfies all the 8 axioms

# ANALOG IMAGES AS VECTORS

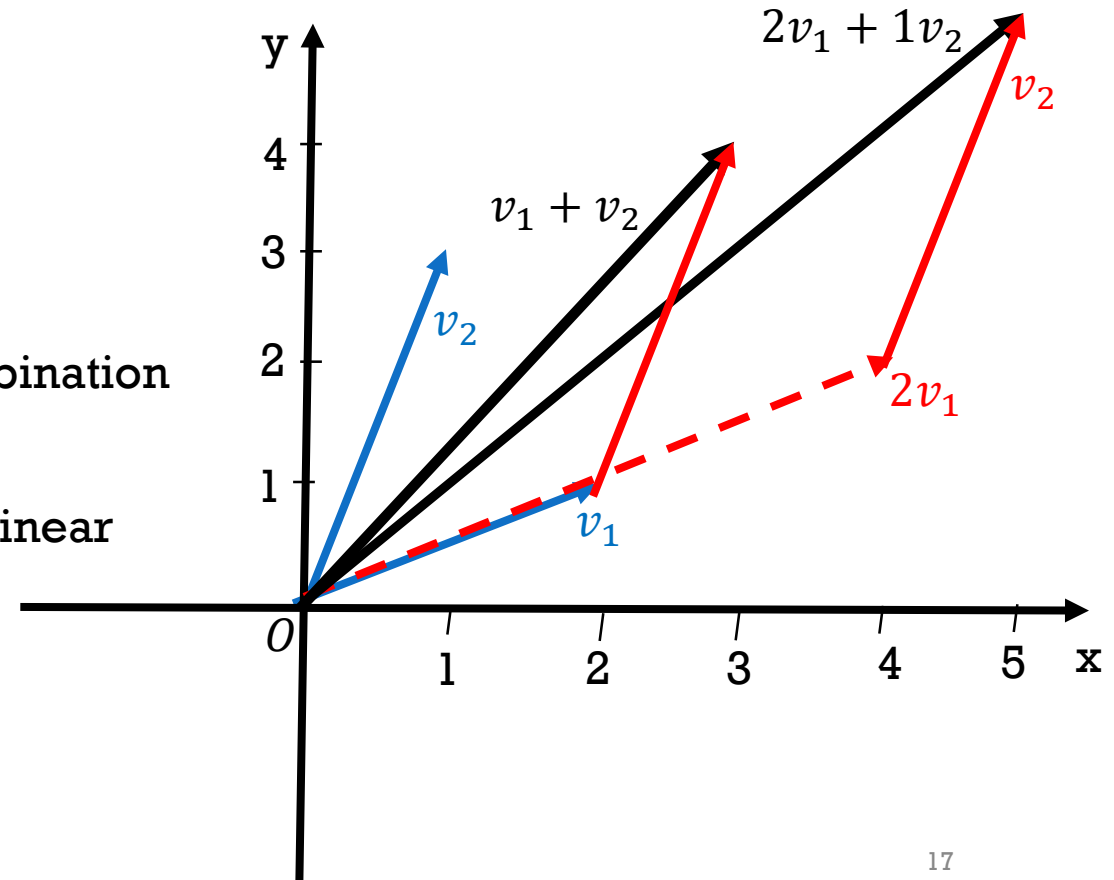
- Take  $V$  as the set of all functions  $f(x, y)$  of two real variables  $(x, y)$ , where
  - $(x, y)$  are the coordinates of a point in the x-y plane, i.e., the location of a “pixel”
  - $f(x, y)$  represents the value of that “pixel”
  - “Pixels” are “points with intensity/color” rather than squares with average intensity/color
- View each such function  $f$  as an (abstract) vector
- Addition of two vectors is addition of two functions:  $f + g$ 
  - $(f + g)(x, y) \stackrel{\text{def}}{=} f(x, y) + g(x, y)$
- Multiplying a vector (i.e., a function  $f$ ) by a number  $a$ :  $(af)(x, y) \stackrel{\text{def}}{=} a \cdot f(x, y)$
- The zero vector (or function)  $O$  is the zero function  $f$  where  $f(x, y) = 0 \forall (x, y)$
- The opposite vector of  $f$  is  $-f$  where  $(-f)(x, y) \stackrel{\text{def}}{=} -f(x, y)$  // negative image
- One can show that this  $(V, +, \cdot, O)$  is a vector space, i.e., satisfies all the 8 axioms



# VECTOR SPACE CONCEPTS

## -- LINEAR COMBINATIONS --

- Let  $(V, +, \cdot, 0)$  be a vector space, and let  $n$  be a positive integer or infinity  $\infty$
- A vector  $v$  is called a **linear combination** of vectors  $v_1, v_2, \dots, v_n$  if we can find  $n$  numbers  $x_1, x_2, \dots, x_n$  such that
  - $v = x_1 v_1 + x_2 v_2 + \dots + x_n v_n$
- Examples:
  - Take  $v_1 = (2,1)$ , and  $v_2 = (1,3)$
  - The vector  $v = 2v_1 + 1v_2 = (5,5)$  is a linear combination of  $v_1$  and  $v_2$
  - Also:  $v = 1v_1 + 1v_2 = v_1 + v_2 = (3,4)$  is another linear combination of  $v_1$  and  $v_2$



# VECTOR SPACE CONCEPTS

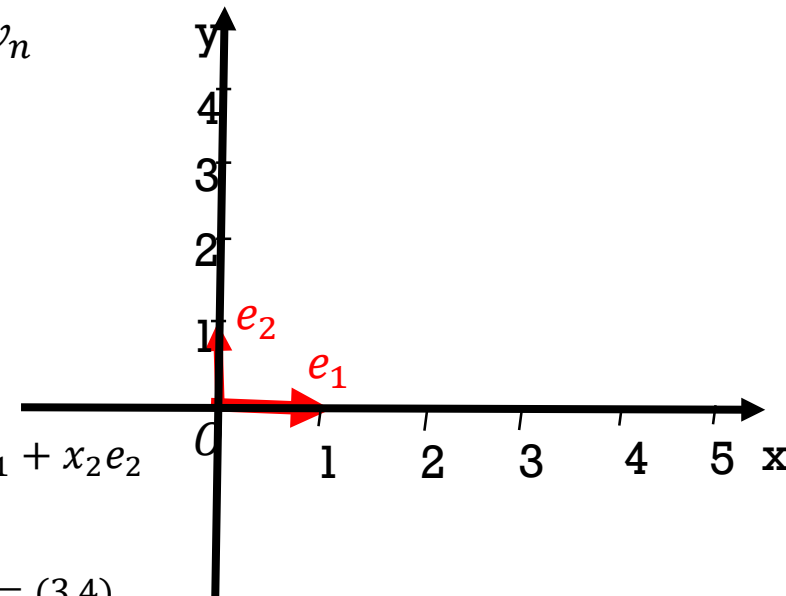
## -- LINEAR INDEPENDENT VECTORS--

- Let  $(V, +, \cdot, 0)$  be a vector space, and let  $n$  be a positive integer or infinity  $\infty$
- A subset of non-zero vectors  $v_1, v_2, \dots, v_n$  are called **linearly independent** if
  - No vector in that subset can be expressed as a linear combination of other vectors in that subset
  - That is, if  $x_1 v_1 + x_2 v_2 + \dots + x_n v_n = 0$ , then we must have  $x_1 = x_2 = \dots = x_n = 0$
- Examples:
  - Take  $v_1 = (2,1), v_2 = (1,3)$ 
    - $v_1, v_2$  are linearly independent (simply prove that if  $x_1 v_1 + x_2 v_2 = 0$ , then we must have  $x_1 = x_2 = 0$ )
  - Take  $v_1 = (2,1), v_2 = (1,3), v_3 = (5,5)$ 
    - $v_1, v_2, v_3$  are NOT linearly independent because  $v_3$  can indeed be expressed as a linear combination of  $v_1, v_2$ :  $v_3 = 2v_1 + 1v_2$
    - Equivalently:  $2v_1 + 1v_2 + (-1)v_3 = 0$  even though  $2 \neq 0, 1 \neq 0, -1 \neq 0$
    - In that case, we say that  $v_1, v_2, v_3$  are **linearly dependent**

# VECTOR SPACE CONCEPTS

## -- BASIS --

- Let  $(V, +, \cdot, 0)$  be a vector space, and let  $n$  be a positive integer or infinity  $\infty$
- A subset of non-zero vectors  $v_1, v_2, \dots, v_n$  is called **a basis** of  $V$  if
  - $v_1, v_2, \dots, v_n$  are linearly independent, and
  - For every vector  $v \in V$ ,  $v$  can be expressed as a linear combination of  $v_1, v_2, \dots, v_n$ , that is, we can find  $n$  numbers  $x_1, x_2, \dots, x_n$  such that  $v = x_1 v_1 + x_2 v_2 + \dots + x_n v_n$
- Example:
  - Take  $V = \mathbb{R}^2 = \mathbb{R} \times \mathbb{R}$
  - The vectors  $e_1 = (1,0)$  and  $e_2 = (0,1)$  form a basis of  $\mathbb{R}^2$ 
    - You can show that  $e_1, e_2$  are linearly independent (prove it)
    - Also, for every vector  $v = (x, y) = (x_1, x_2)$ , we can express  $v = x_1 e_1 + x_2 e_2$ 
      - Example:  $(3,4) = 3e_1 + 4e_2$ 
        - Proof:  $3e_1 + 4e_2 = 3(1,0) + 4(0,1) = (3,0) + (0,4) = (3+0, 0+4) = (3,4)$



# VECTOR SPACE CONCEPTS

## -- BASIS IS NOT UNIQUE NOR GUARANTEED --

- Let  $(V, +, \cdot, 0)$  be a vector space, and let  $n$  be a positive integer or infinity  $\infty$

- $V$  is not guaranteed to have a basis

- On the other hand, if  $V$  has a basis, it can have many bases

- Example: Take  $V = \mathbb{R}^2 = \mathbb{R} \times \mathbb{R}$

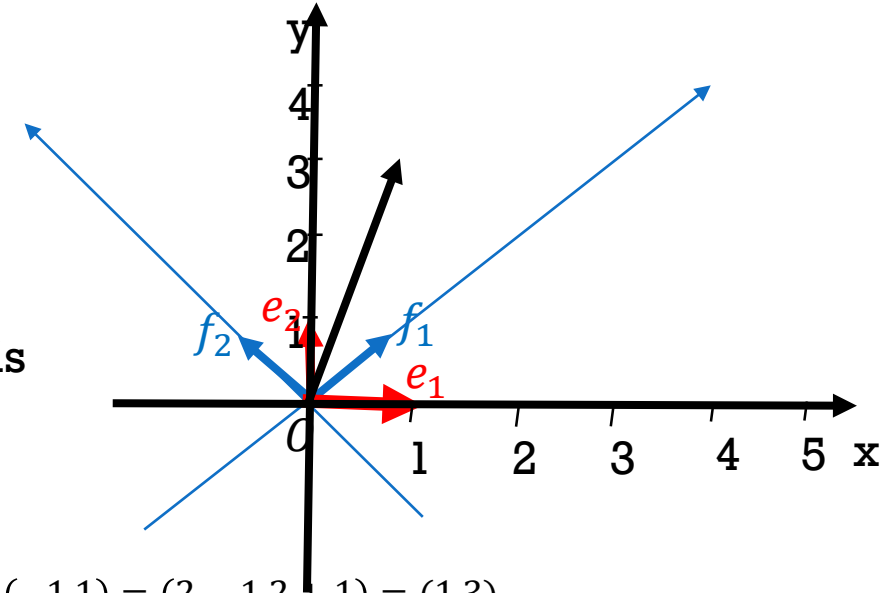
- The vectors  $e_1 = (1,0)$  and  $e_2 = (0,1)$  form a basis of  $\mathbb{R}^2$

- Also, the vectors  $f_1 = (1,1)$  and  $f_2 = (-1,1)$  form another basis

- For every vector  $v = (x, y)$ , we can express  $v$  as

- $v = x_1 f_1 + x_2 f_2$  where  $x_1 = \frac{x+y}{2}$  and  $x_2 = \frac{y-x}{2}$  (prove it)

- Ex:  $(1,3) = 2f_1 + 1f_2$  because  $2f_1 + 1f_2 = 2(1,1) + 1(-1,1) = (2,2) + (-1,1) = (2-1, 2+1) = (1,3)$



- A given basis  $v_1, v_2, \dots, v_n$  is like an axis system:

- The coefficients of  $x_1, x_2, \dots, x_n$  of  $v = x_1 v_1 + x_2 v_2 + \dots + x_n v_n$  are viewed as the **coordinates** of  $v$  wrt to that basis (or that axis system)

- Ex: the basis  $e_1 = (1,0)$  and  $e_2 = (0,1)$  corresponds to the x-y axes
- Vector  $(1,3) = 1e_1 + 3e_2$  has coordinates 1 and 3 wrt basis  $e_1$  and  $e_2$

- Another basis is like another axis system

Vector  $(1,3) = 2f_1 + 1f_2$  has coordinates 2 and 1 wrt basis  $f_1, f_2$

# MORE ON VECTOR SPACE BASES

## -- CANONICAL BASIS OF $\mathbb{R}^n$ --

- $\mathbb{R}^3 = \mathbb{R} \times \mathbb{R} \times \mathbb{R}$  has as a basis  $e_1, e_2, e_3$  where
  - $e_1 = (1,0,0), e_2 = (0,1,0), e_3 = (0,0,1)$
- $\mathbb{R}^n = \underbrace{\mathbb{R} \times \mathbb{R} \times \cdots \times \mathbb{R}}_{n \text{ times}}$  has as a basis  $e_1, e_2, \dots, e_n$  where
  - $e_1 = (1,0, \dots, 0), e_2 = (0,1,0, \dots, 0), \dots, e_i = (0, \dots, 0, 1, 0, \dots, 0), \text{ and } e_n = (0, \dots, 0, 1)$
  - We call this basis the **canonical basis** of  $\mathbb{R}^n$  (i.e., the “natural” basis)
  - That is because for any vector  $(x_1, x_2, \dots, x_n) \in \mathbb{R}^n$ , the coordinates of that vector wrt the canonical basis  $e_1, e_2, \dots, e_n$  are simply the components of the vector:
    - $(x_1, x_2, \dots, x_n) = x_1 e_1 + x_2 e_2 + \cdots + x_n e_n$
  - Whereas for any other basis  $f_1, f_2, \dots, f_n$ , the coordinates of  $(x_1, x_2, \dots, x_n)$  wrt  $f_1, f_2, \dots, f_n$  are not  $x_1, x_2, \dots, x_n$

# DIMENSION OF A VECTOR SPACE

- If a vector space  $(V, +, \cdot, 0)$  has a basis of some  $n$  vectors, then
  - **Theorem:** Every basis of  $V$  will have  $n$  vectors, for the same value of  $n$
  - We say  $n$  is the **dimension** of  $V$ , and  $V$  an  $n$ -dimensional ( $n$ D) space
  - $n$  can be finite or infinite
- Examples:
  - $\mathbb{R}^n$  is of dimension  $n$  (because the canonical basis  $e_1, e_2, \dots, e_n$  of  $\mathbb{R}^n$  has  $n$  vectors)
  - $\mathbb{R}^{n \times m}$  is a vector space of dimension  $n \times m$
- Notes about terminology:
  - Before, we would refer to audio signals as 1D signals, and to images as 2D signals
  - Now, in vectors spaces, 1D audio signals of  $n$  samples form an  $n$ -dimensional ( $n$ D) space, and 2D images form an  $n \times m$ - dimensional space
  - This can be confusing, but the context makes things clear:
    - 1D **signals** vs.  $n$ D **vectors**
    - 2D **images** vs.  $(n \times m)$ D **vectors**

# CANONICAL BASIS VS. OTHER BASES OF $\mathbb{R}^n$ --

## COMPRESSION-DESIRABLE BASES OF $\mathbb{R}^n$ --

- The canonical basis of  $\mathbb{R}^n$  is great in geometry and form a convenient representation of vectors, but it is terribly poor for compression
- We seek alternative bases that will be more suitable for lossy compression
- It would be great to have a basis  $f_1, f_2, \dots, f_n$  for  $\mathbb{R}^n$  such that for any “natural” signal  $x = (x_1, x_2, \dots, x_n)$ , we can express  $x$  as a linear combination of  $f_1, f_2, \dots, f_n$  such that
  - $x = y_1 f_1 + y_2 f_2 + \dots y_n f_n$
  - The human eyes/ears are more sensitive to certain  $f_i$ 's and less sensitive to other  $f_i$ 's, e.g.,
    - More sensitive to  $f_1, f_2, f_3$  and less sensitive to  $f_4, f_5, \dots$
  - I.e., some basis vectors are more important, and others less important, to human senses
  - Then, we can drop the less important  $f_i$ 's (i.e., replace the corresponding  $y_i$ 's with 0's)
  - And approximate  $x$  by the remaining (important vectors), e.g.,  $x \approx y_1 f_1 + y_2 f_2 + y_3 f_3$
  - Or quantize the less important  $y_i$ 's aggressively (to get more compression), and the more important  $y_i$ 's lightly (to retain reconstruction quality)

# EXISTANCE OF COMPRESSION-DESIRABLE BASES OF $\mathbb{R}^n$

- We will see that such compression-desirable bases do exist
- We will see also how the transforms we studied are connected to desirable bases
- But, first, let's see how a linear transform relates to bases in vector spaces
- That is the subject of the next few slides



# 1D SIGNALS AND COLUMN/MATRIX NOTATION

- Recall that a 1D signal  $x$  (like an audio signal) of  $n$  components is viewed as a vector  $x = (x_1, x_2, \dots, x_n)$  in an  $n$ -dimensional vector space
- We will represent each such signal as a column vector:

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

- Note: In some situations, it is more convenient to start the indexing from 0 instead of 1
- To save on vertical space, we sometimes write  $x = [x_1, x_2, \dots x_n]^T$
- Also, each vector in  $\mathbb{R}^n$ , including each basis vector (for whatever basis), will be represented as a column vector

# MATRICES AS A SEQUENCE OF COLUMN VECTORS

- A matrix  $A = (a_{ij})_{\substack{1 \leq i \leq n \\ 1 \leq j \leq m}}$ , or simply  $A = (a_{ij})$  when the number of rows and columns of  $A$  are known, is

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \quad // \text{ again, sometimes the indexing starts from 0}$$

- The matrix  $A$  can be viewed as a sequence of columns:

$$A = \begin{bmatrix} \boxed{\begin{matrix} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{matrix}} & \boxed{\begin{matrix} a_{12} \\ a_{22} \\ \vdots \\ a_{n2} \end{matrix}} & \cdots & \boxed{\begin{matrix} a_{1m} \\ a_{2m} \\ \vdots \\ a_{nm} \end{matrix}} \end{bmatrix} = [C_1 \ C_2 \ \cdots \ C_m] \text{ where } C_1 = \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{bmatrix}, C_2 = \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{n2} \end{bmatrix}, \dots, C_m = \begin{bmatrix} a_{1m} \\ a_{2m} \\ \vdots \\ a_{nm} \end{bmatrix}$$

$\uparrow \quad \quad \uparrow \quad \quad \uparrow$   
 $C_1 \quad C_2 \quad C_m$

# MATRIX MULTIPLICATION

- Let  $A = (a_{ij})$  be an  $n \times m$  matrix, and  $B = (b_{ij})$  be a  $m \times r$  matrix
- The product  $AB$  is a  $n \times r$  matrix  $C = (c_{ij})$  where
  - $c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots a_{im}b_{mj}$  (inner product of row  $i$  of  $A$  and column  $j$  of  $B$ )

$$\bullet \quad C = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1r} \\ b_{21} & b_{22} & \cdots & b_{2r} \\ \vdots & \ddots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mr} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1r} \\ c_{21} & c_{22} & \cdots & c_{2r} \\ \vdots & \ddots & \boxed{c_{ij}} & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nr} \end{bmatrix}$$

# MATRIX-COLUMN MULTIPLICATION

- Let  $A = (a_{ij})$  be an  $n \times n$  matrix,  $x = [x_1, x_2, \dots, x_n]^T$  be a column
- The product  $Ax$  is a column  $y = [y_1, y_2, \dots, y_n]^T = Ax$  where
  - $y_i = a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = [C_1 \ C_2 \ \dots \ C_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 C_1 + x_2 C_2 + \dots + x_n C_n$$

$\begin{matrix} \uparrow & \uparrow & & \uparrow \\ C_1 & C_2 & & C_n \end{matrix}$

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$$

$$A^{-1} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & d_{nn} \end{bmatrix}$$

$$\text{Similarly, } x = A^{-1}y = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & d_{nn} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = [f_1 \ f_2 \ \dots \ f_n] \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = y_1 f_1 + y_2 f_2 + \dots + y_n f_n$$

$\begin{matrix} \uparrow & \uparrow & & \uparrow \\ f_1 & f_2 & & f_n \end{matrix}$

# CONNECTION WITH TRANSFORMS

- Recall that a transform is characterized by a square matrix  $A = (a_{ij})$
- The transform of a signal  $x = [x_1, x_2, \dots, x_n]^T$  is  $y = Ax$
- The inverse transform of  $y = [y_1, y_2, \dots, y_n]^T$  is  $x = A^{-1}y$
- Based on the previous slide, we have:

$$x = A^{-1}y = \begin{bmatrix} d_{11} \\ d_{21} \\ \vdots \\ d_{n1} \end{bmatrix} \begin{bmatrix} d_{12} \\ d_{22} \\ \ddots \\ d_{n2} \end{bmatrix} \cdots \begin{bmatrix} d_{1n} \\ d_{2n} \\ \vdots \\ d_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = [f_1 \ f_2 \ \cdots \ f_n] \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = y_1 f_1 + y_2 f_2 + \cdots y_n f_n$$

- That is,  $x = y_1 f_1 + y_2 f_2 + \cdots y_n f_n$

- $f_1, f_2, \dots, f_n$  are a new basis of  $\mathbb{R}^n$
- $f_1, f_2, \dots, f_n$  are the columns of the inverse matrix  $A^{-1}$  of the transform

- Therefore:  **$y_1, y_2, \dots, y_n$  are the coordinates of vector  $x$  wrt to the basis  $f_1, f_2, \dots, f_n$**

# TRANSFORMS AND BASES

- We saw earlier for vector/signal  $x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$ :
- $x_1, x_2, \dots, x_n$  are the coordinates of vector  $x$  wrt to the canonical basis  $e_1, e_2, \dots, e_n$

$$e_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \dots, e_i = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \dots, e_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix},$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 e_1 + x_2 e_2 + \dots + x_n e_n = x_1 \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \dots + x_n \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$$

- From the previous slide,

$$\text{if } y = Ax, A^{-1} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & d_{nn} \end{bmatrix}, \text{ then:}$$

$f_1 \quad f_2 \quad \dots \quad f_n$

$y_1, y_2, \dots, y_n$  are the coordinates of vector  $x$  wrt to the basis  $f_1, f_2, \dots, f_n$

$$x = y_1 f_1 + y_2 f_2 + \dots + y_n f_n$$

- Therefore, a **transform** characterized by a matrix  $A$  is:
  - A change of basis, from the canonical basis  $e_1, e_2, \dots, e_n$  to a new basis  $f_1, f_2, \dots, f_n$  determined by  $A^{-1}$**
  - That is, a change of coordinate systems**

# VISUALIZATION OF THE BASIS VECTORS OF A TRANSFORM

- Take the transform matrix  $A$
- Get its transform matrix  $A^{-1}$
- Extract the columns of  $A^{-1}$ :  $f_1 f_2 \dots f_n$ 
  - Or, indexing from 0, rename them  $f_0 f_1 \dots f_{n-1}$
- Plot each  $f_i$  where the horizontal axis is  $0, 1, 2, \dots, n - 1$ , and the vertical axis corresponds to the values of the components of  $f_i$
- There should be  $n$  plots, one per basis vector

# THE BASIS VECTORS OF THE FOURIER TRANSFORM FOR N=8

- $a_{kl} = \sqrt{\frac{1}{N}} e^{-\frac{2\pi i}{N} kl} = \sqrt{\frac{1}{N}} \left( \cos \frac{2\pi}{N} kl - i \sin \frac{2\pi}{N} kl \right), \forall k, l = 0, 1, 2, \dots, N - 1$

- $a = \frac{\sqrt{2}}{2} (1 + i)$  and  $\bar{a} = \frac{\sqrt{2}}{2} (1 - i)$

$$A_8 = \sqrt{\frac{1}{8}} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & \bar{a} & -i & -a & -1 & -\bar{a} & i & a \\ 1 & -i & -1 & i & 1 & -i & -1 & i \\ 1 & -a & i & \bar{a} & -1 & a & -i & -\bar{a} \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -\bar{a} & -i & a & -1 & \bar{a} & i & -a \\ 1 & i & -1 & -i & 1 & i & -1 & -i \\ 1 & a & i & -\bar{a} & -1 & -a & -i & \bar{a} \end{bmatrix} \quad A^{-1} = \sqrt{\frac{1}{8}} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & a & i & -\bar{a} & -1 & -a & -i & \bar{a} \\ 1 & i & -1 & -i & 1 & i & 1 & -i \\ 1 & -\bar{a} & -i & a & -1 & \bar{a} & i & -a \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -a & i & \bar{a} & -1 & a & -i & -\bar{a} \\ 1 & -i & 1 & i & 1 & -i & -1 & i \\ 1 & \bar{a} & -i & -a & -1 & -\bar{a} & i & a \end{bmatrix}$$

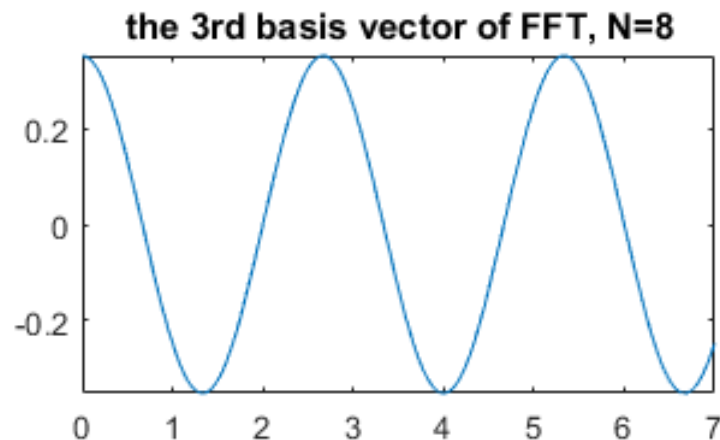
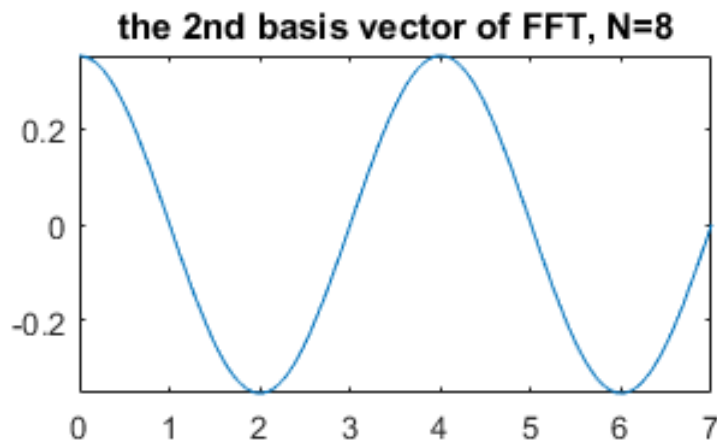
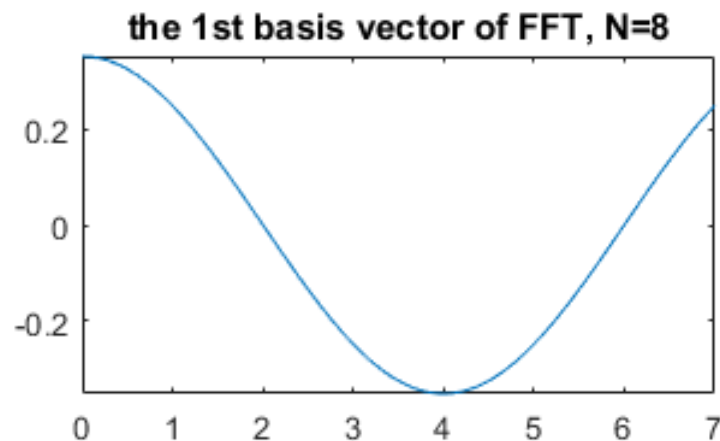
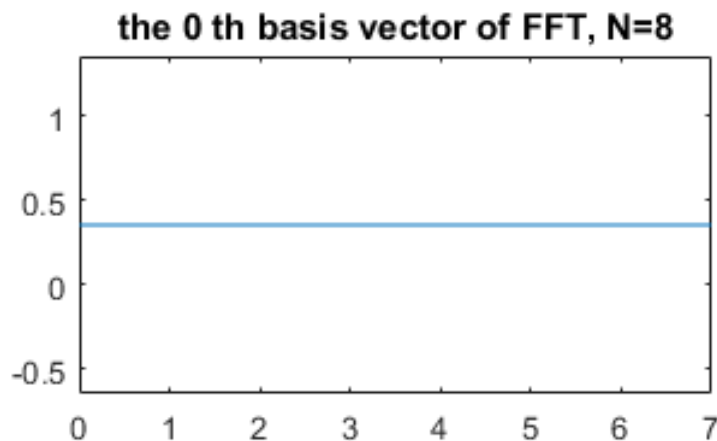


# THE BASIS VECTORS OF FOURIER TRANSFORM

- $A_N^{-1} = \text{conjugate}(A_N) = (\sqrt{\frac{1}{N}} e^{\frac{2\pi i}{N} kl}) = \sqrt{\frac{1}{N}} (\cos \frac{2\pi}{N} kl + i \sin \frac{2\pi}{N} kl), \forall k, l = 0, 1, 2, \dots, N - 1$
- Because the entries involve complex numbers, we can't plot them
- But we can plot the real-part:  $(\sqrt{\frac{1}{N}} \cos \frac{2\pi}{N} kl) \forall k, l = 0, 1, 2, \dots, N - 1$
- $\forall l = 0, 1, 2, \dots, N - 1$ , take real-part of the  $l^{\text{th}}$  basis vector:  $f_l(k) = \sqrt{\frac{1}{N}} \cos \frac{2\pi}{N} kl$
- It is more insightful to plot each basis vector  $f_l(k) = \sqrt{\frac{1}{N}} \cos \frac{2\pi}{N} kl$  as a continuous function of  $k$  (or of  $x$ ):  $f_l(x) = \sqrt{\frac{1}{N}} \cos \frac{2\pi}{N} lx$ , for  $N = 8, l = 0, 1, \dots, 7$

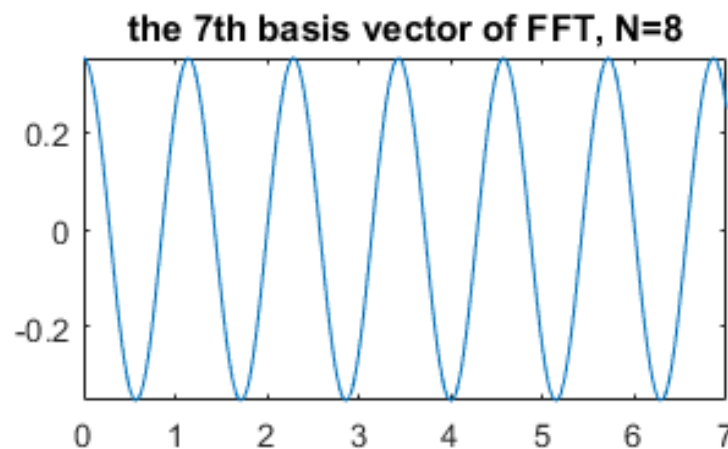
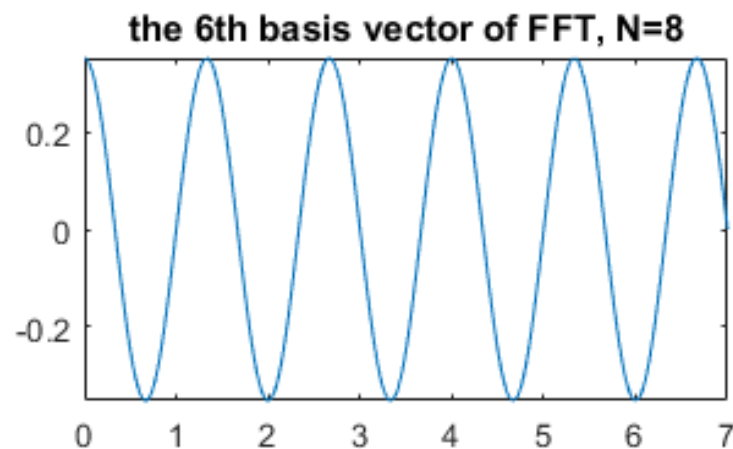
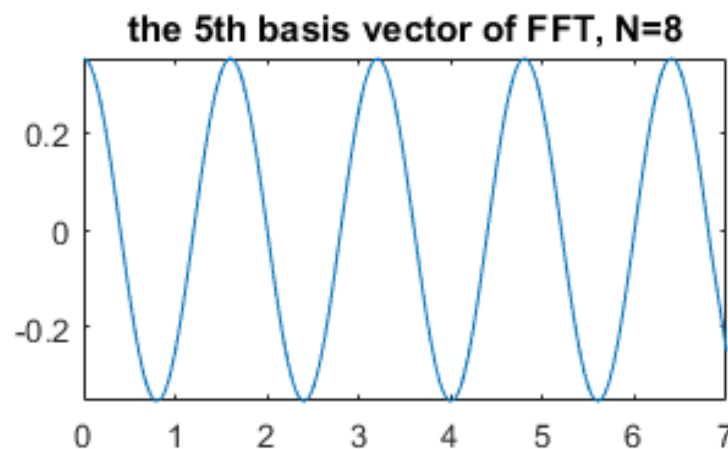
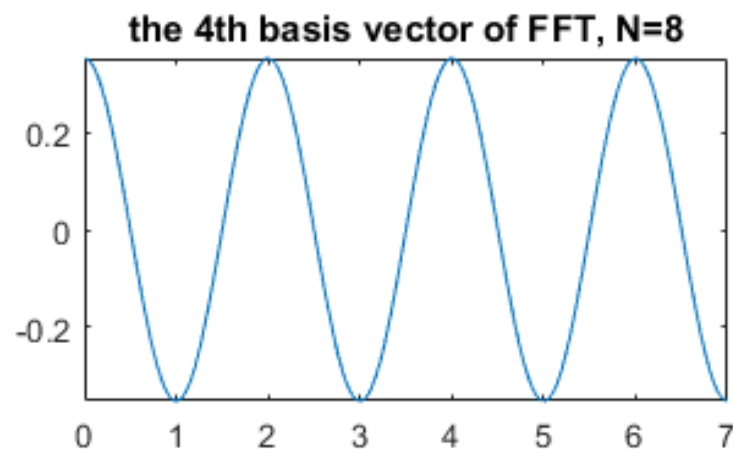
# THE REAL-PART OF THE BASIS VECTORS OF FFT, N=8 (1/2)

- The first 4 basis vectors (shown as continuous plots of the real part)



# THE REAL-PART OF THE BASIS VECTORS OF FFT, N=8 (2/2)

- The second 4 basis vectors (shown as continuous plots of the real part)

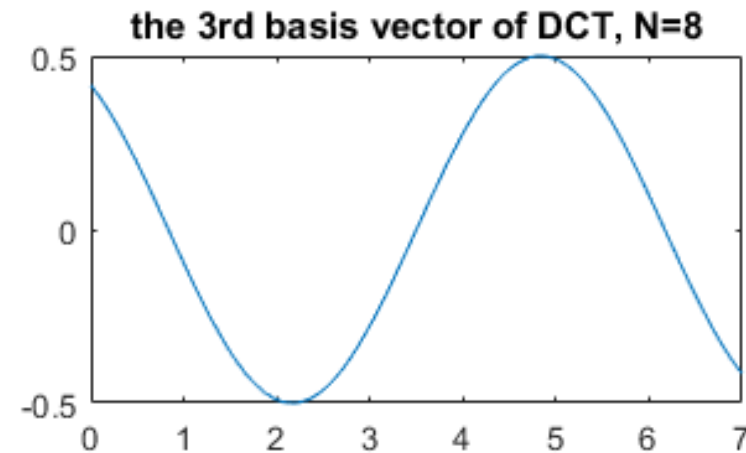
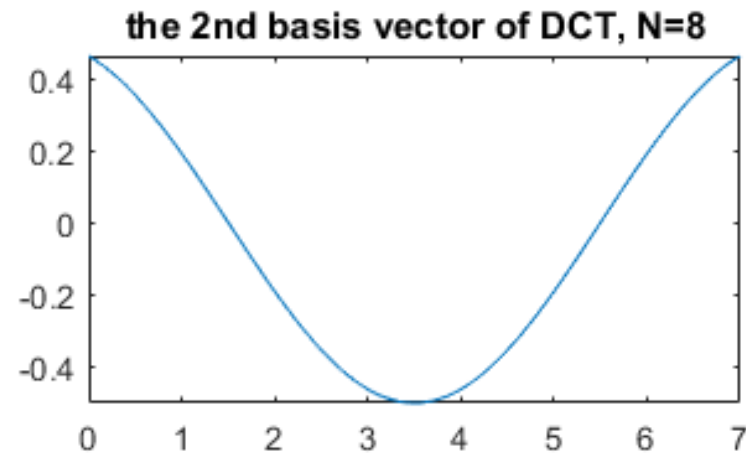
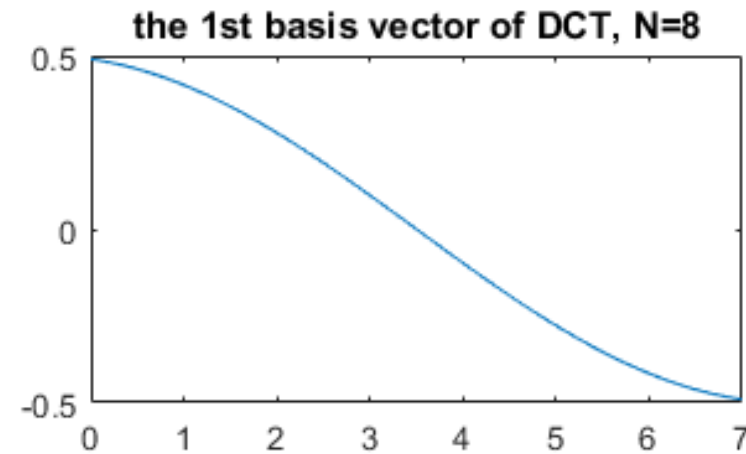
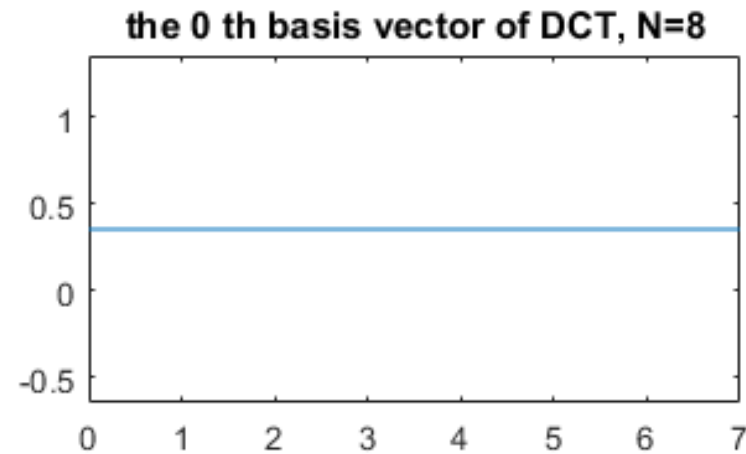


# THE BASIS VECTORS OF DCT OF SIZE N=8

- $a_{0l} = \sqrt{\frac{1}{N}}$  for all  $l = 0, 1, \dots, N - 1$ ;
  - $a_{kl} = \sqrt{\frac{2}{N}} \cos \frac{\left(l + \frac{1}{2}\right)k\pi}{N} \quad \forall k = 1, 2, \dots, N - 1, \text{ and } l = 0, 1, \dots, N - 1$
  - $A_N^{-1} = A_N^T$
  - $f_k = \text{Col}_k(A_N^{-1}) = \text{Row}_k(A_N) = (a_{kl})$  for  $l = 0, 1, \dots, N - 1$
  - $f_0 = \sqrt{\frac{1}{N}} [1 \ 1 \ \dots \ 1]^T$ , and for  $k \geq 1$ :
  - $f_k = \sqrt{\frac{2}{N}} \left[ \cos \frac{\left(\frac{1}{2}\right)k\pi}{N}, \cos \frac{\left(1 + \frac{1}{2}\right)k\pi}{N}, \cos \frac{\left(2 + \frac{1}{2}\right)k\pi}{N}, \dots, \cos \frac{\left(N - 1 + \frac{1}{2}\right)k\pi}{N} \right]^T$
- Let  $\alpha_0 = \sqrt{\frac{1}{N}}$ , and  $\alpha_k = \sqrt{\frac{2}{N}}$  for  $k \geq 1$
  - $f_k(x) = \alpha_k \cos \frac{\left(x + \frac{1}{2}\right)k\pi}{N}$
  - We will plot  $f_k(x)$  as a continuous function of  $x$ , for  $N=8, k = 1, 2, \dots, 7$

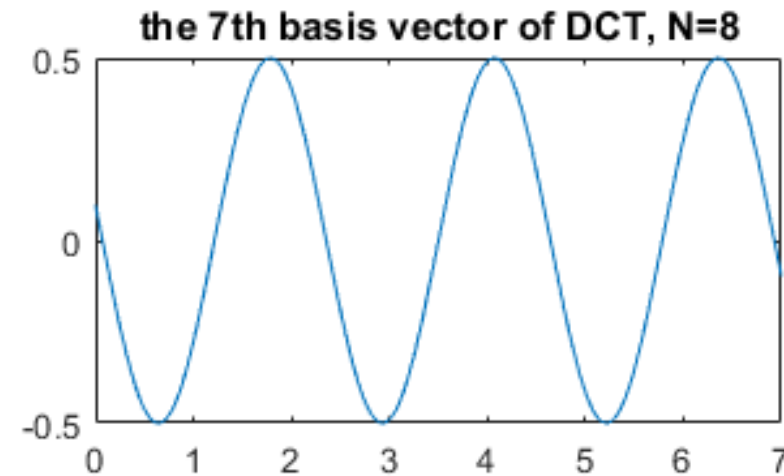
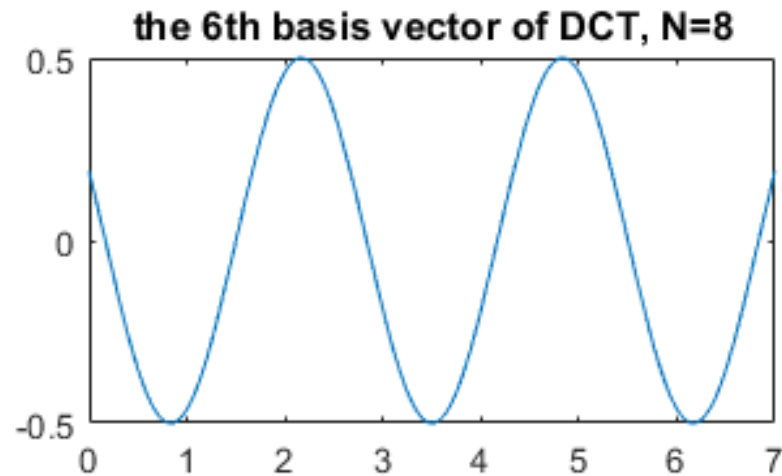
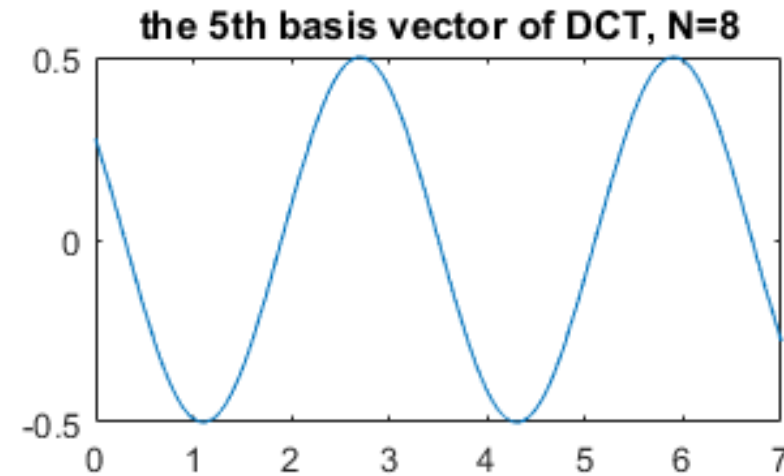
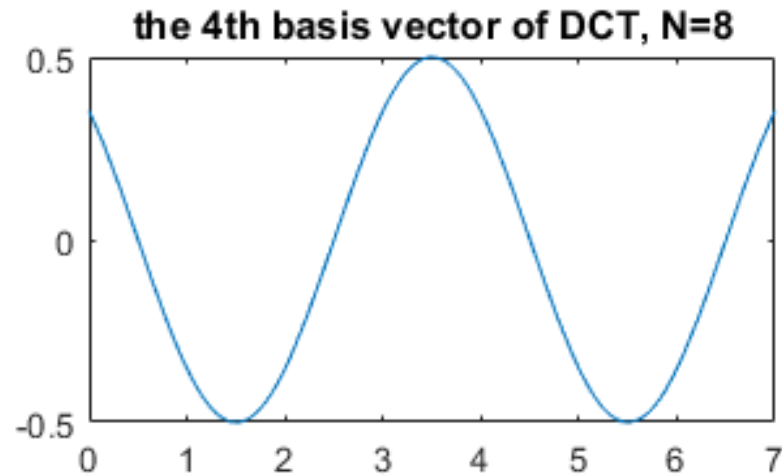
# THE BASIS VECTORS OF DCT OF SIZE N=8 (1/2)

- The first 4 basis vectors (shown as continuous plots)



# THE BASIS VECTORS OF DCT OF SIZE N=8 (2/2)

- The second 4 basis vectors (shown as continuous plots)



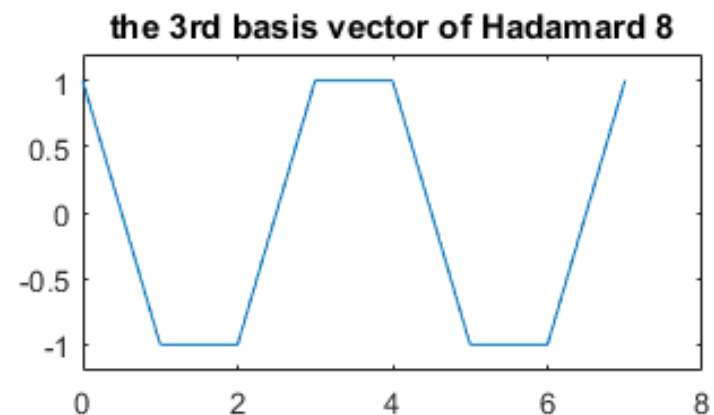
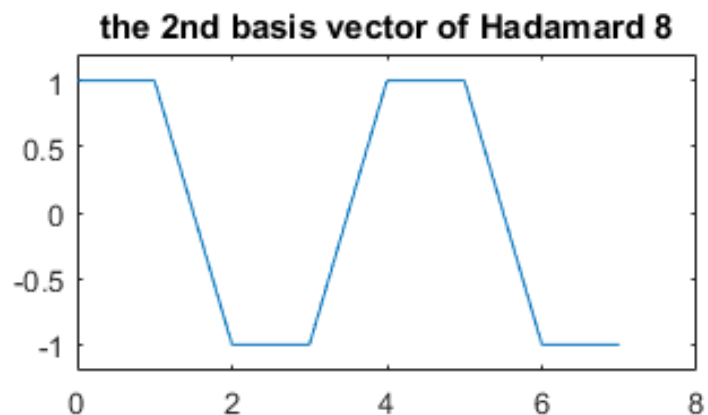
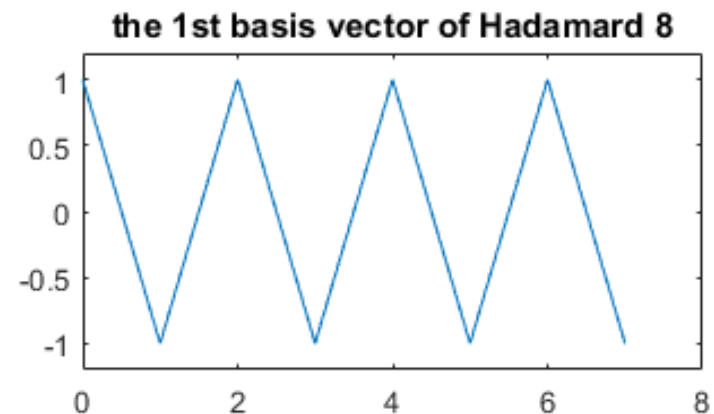
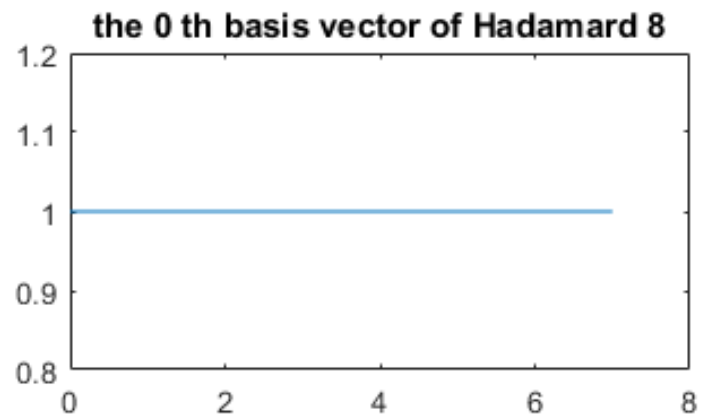
# THE MATRIX OF THE HADAMARD TRANSFORM FOR N=8

- $A_N^{-1} = A_N^T = A_N$

$$A_8 = \sqrt{\frac{1}{8}} \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 & 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 \\ 1 & -1 & -1 & 1 & -1 & 1 & 1 & -1 \end{pmatrix}$$

# THE BASIS VECTORS OF HADAMARD FOR N=8 (1/2)

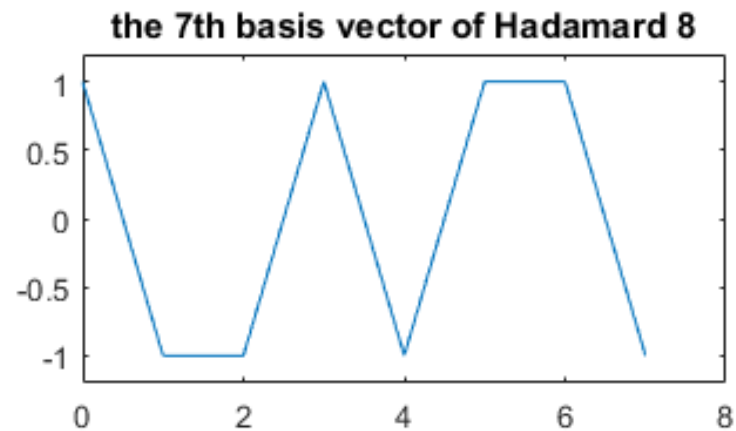
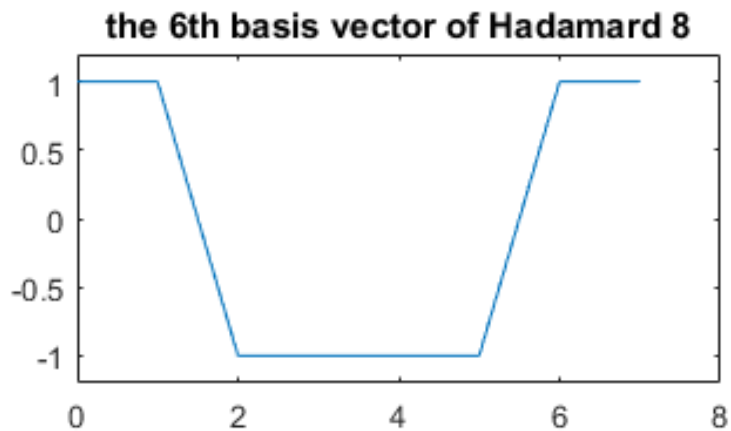
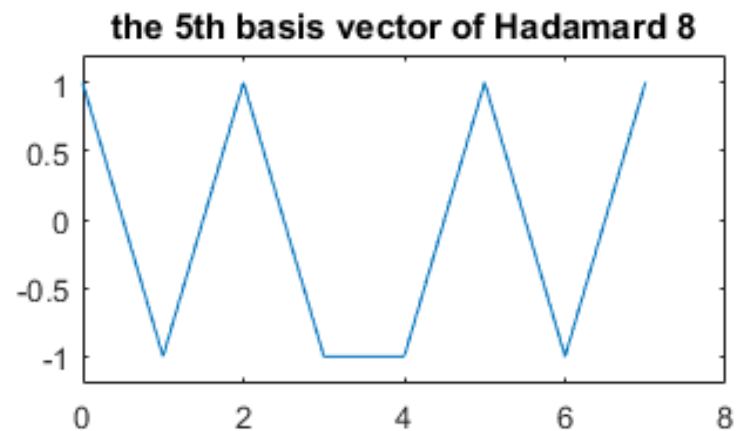
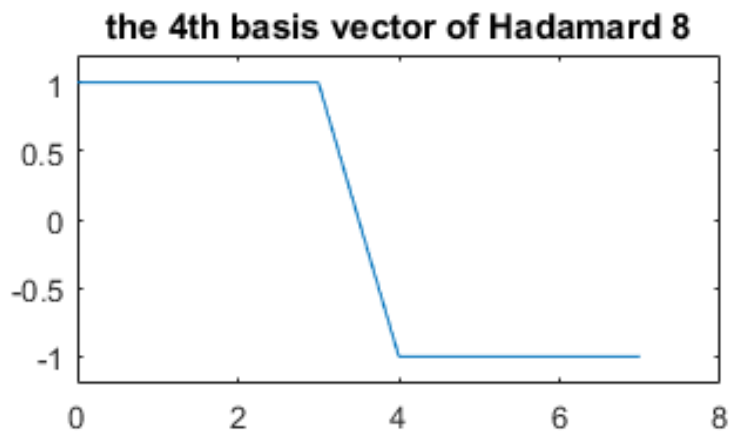
- The first 4 basis vectors





# THE BASIS VECTORS OF HADAMARD FOR N=8 (2/2)

- The second 4 basis vectors



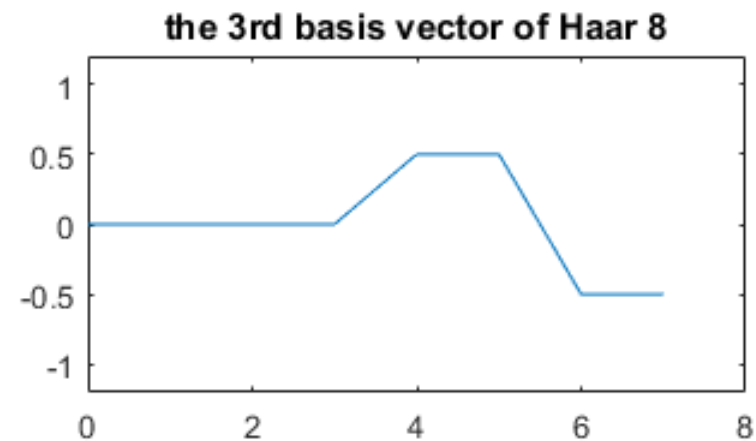
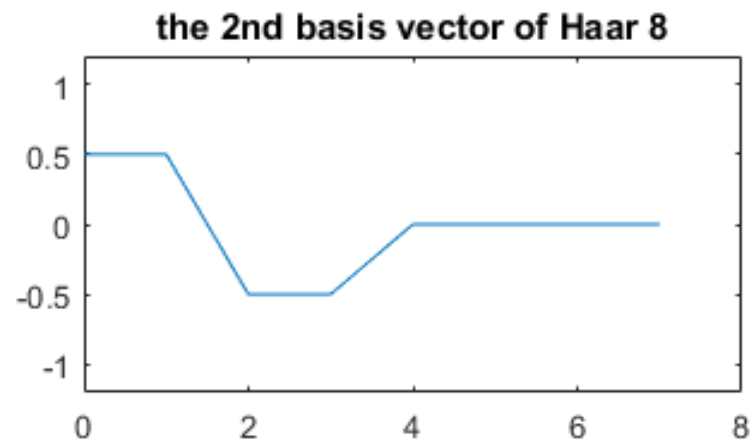
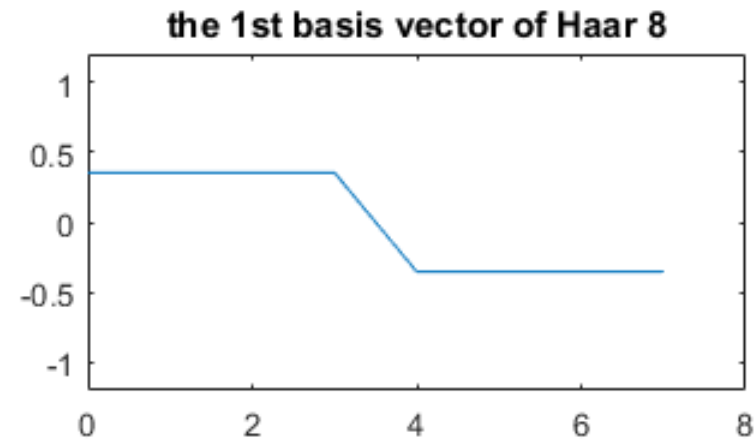
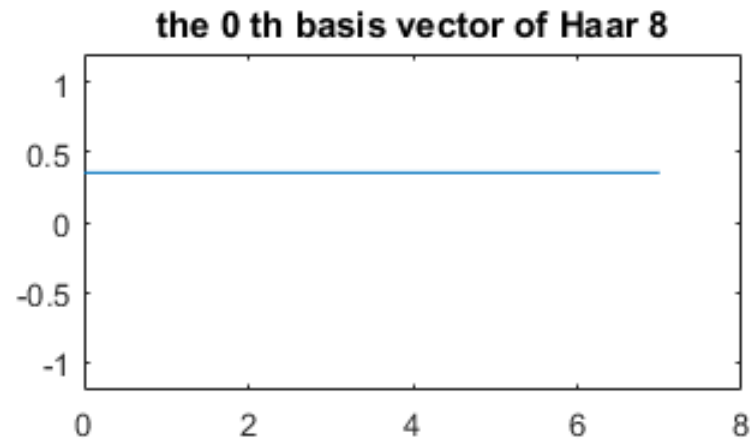
# THE MATRIX OF THE HAAR TRANSFORM FOR N=8

- $A_N^{-1} = A_N^T$
- Therefore,  $f_k = \text{col}_k(A_N^{-1}) = \text{col}_k(A_N^T) = [\text{row}_k(A_N)]^T$

$$A_8 = \sqrt{\frac{1}{8}} \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} \\ 2 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & -2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & -2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & -2 \end{pmatrix}$$

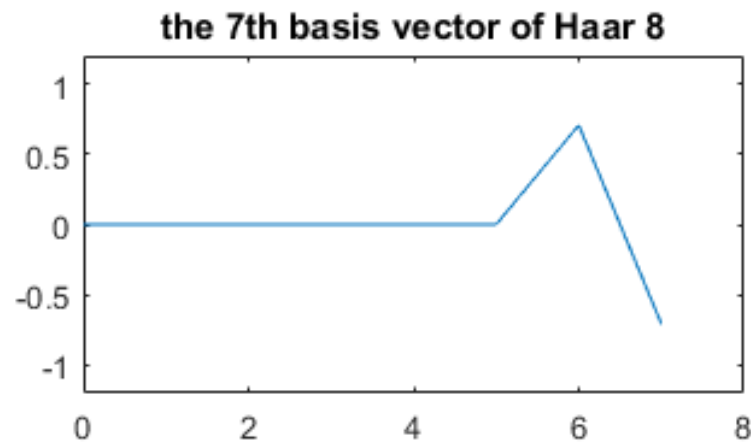
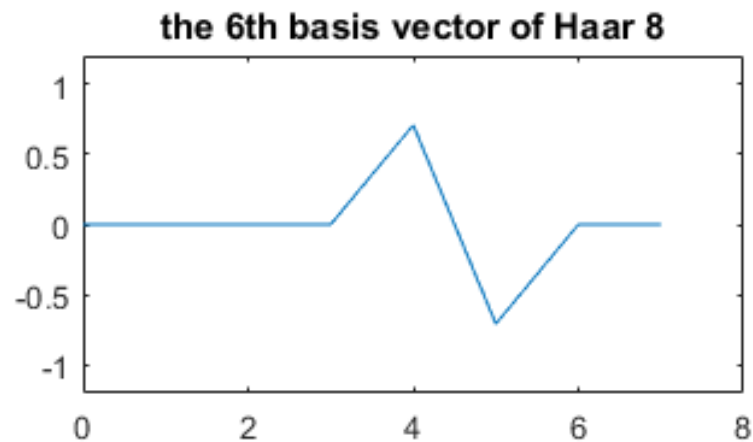
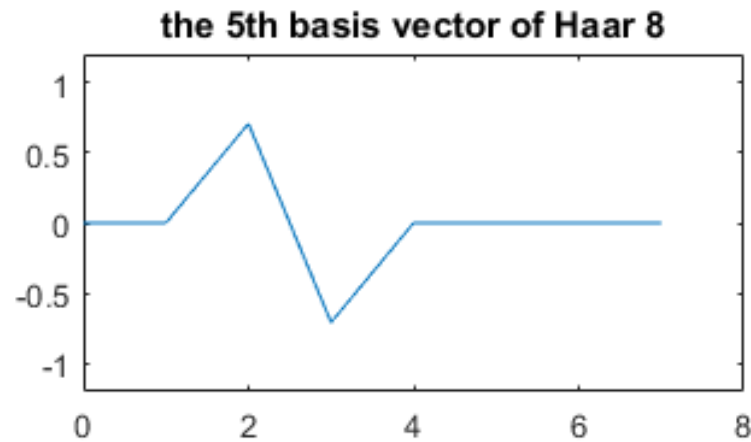
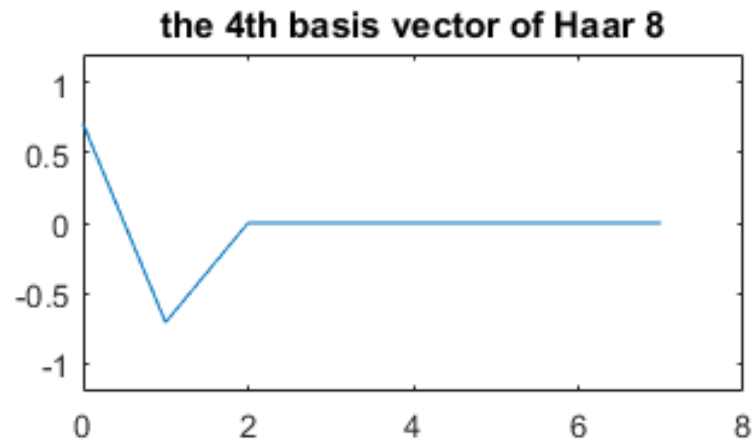
# THE BASIS VECTORS OF HAAR FOR N=8 (1/2)

- The first 4 basis vectors



# THE BASIS VECTORS OF HAAR FOR N=8 (2/2)

- The second 4 basis vectors



# NEXT LECTURE

- Frequency Perspective of Transforms
- Statistical Perspective of Transforms