

# MAT 167: Applied Linear Algebra

Note Title

## LECTURE 01

### Course Objectives:

- \* To learn the importance of linear algebra in practical problems and applications, in particular,
  - machine learning & pattern recognition
  - data mining & search engines
  - signal & image processing
- \* To learn important & useful concepts of linear algebra, e.g.,
  - linear transformations
  - bases & orthogonality
  - projections & least squares method
  - various matrix decompositions  
LU, QR, eigenvalue, and  
SVD (singular value decomposition)
- \* To enhance your understanding of the above concepts & applications through the use of ~~MATLAB~~  
Julia

# Motivation: Vector/Matrix Representation of Datasets

Example 1. Music Signals  
and Signal Compression  
⇒ ~~MATLAB~~ Demo!

Julia

Example 2. Face Image Database  
⇒ Figures

Example 3. Term-Document  
Matrices for Search

Example 4. Link Graphs of  
Webpages

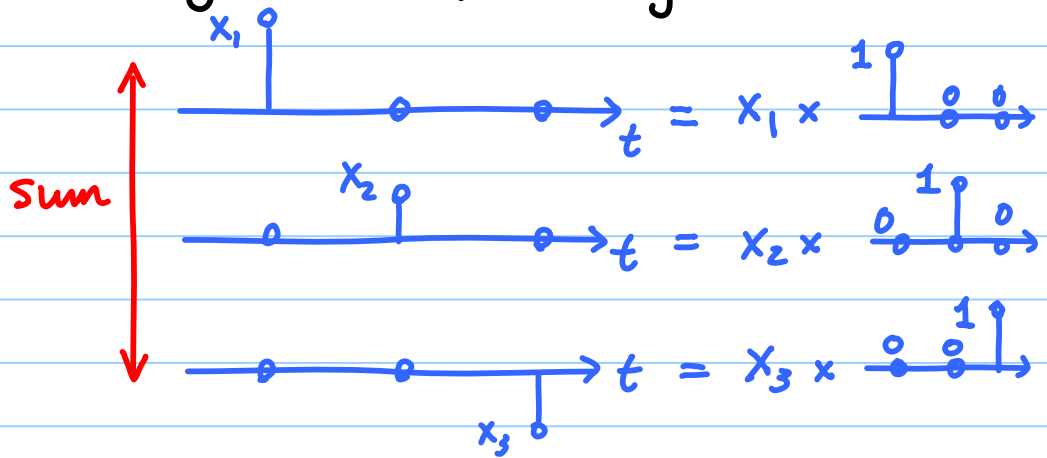
## Example 1: Music Signals & Signal Compression

Consider a very short signal consisting of 3 samples

actual  
music  
signal  
may have  
 $10^6$  samples  
or more

$$\underline{X} = [x_1, x_2, x_3]^T = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$


This vector can be represented exactly as the following sum



$$\begin{aligned} x_1 \times \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \\ x_2 \times \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \\ x_3 \times \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \end{aligned}$$

In other words

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\Leftrightarrow \underline{X} = x_1 \underline{e}_1 + x_2 \underline{e}_2 + x_3 \underline{e}_3$$

Any  $\underline{X} \in \mathbb{R}^3$  can be written exactly  
using the linear combination of  $\underline{e}_1, \underline{e}_2, \underline{e}_3$

This can also be written as

$$\mathbf{x} = \left[ \begin{array}{c|c|c} \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 \end{array} \right] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\text{basis matrix } \mathbf{X}} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

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However, depending on a signal, there may be more efficient way to represent / approximate a given vector  $\mathbf{x}$ .

e.g., consider the following vectors instead of  $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3$ .

def

$$\begin{aligned} \frac{1}{\sqrt{3}} \begin{array}{c} \circ \\ \circ \\ \circ \end{array} \xrightarrow{t} &= \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \equiv \mathbf{u}_1 \\ \frac{1}{\sqrt{2}} \begin{array}{c} \circ \\ 0 \\ -\frac{1}{\sqrt{2}} \end{array} \xrightarrow{t} &= \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \equiv \mathbf{u}_2 \\ \frac{1}{\sqrt{6}} \begin{array}{c} \circ \\ \circ \\ -\frac{2}{\sqrt{6}} \end{array} \xrightarrow{t} &= \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \equiv \mathbf{u}_3 \end{aligned}$$

any  $\mathbf{x} \in \mathbb{R}^3$  can be written this way!

$$\mathbf{x} = a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2 + a_3 \mathbf{u}_3$$

Given  $\mathbf{x}$ , how to compute  $a_1, a_2, a_3$ ?

⇒ We'll learn how when we discuss "orthogonality"!

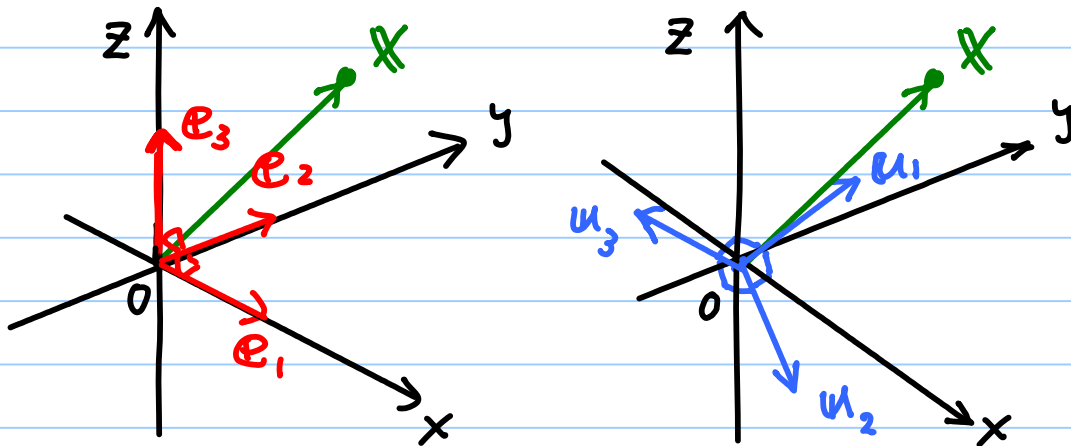
We can also write this as

$$X = \begin{bmatrix} | & | & | \\ u_1 & u_2 & u_3 \\ | & | & | \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & 0 & -\frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

$= U a \Rightarrow a = U^T X$

basis matrix coordinate vector of  $X$  relative to  $U$

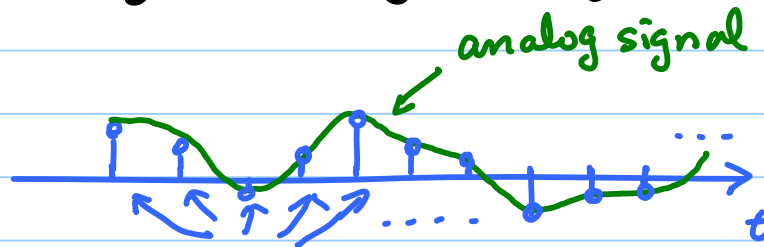
Note



But, we can only visualize such orthogonality up to 3D. The orthogonality can be generalized to any dimension  $\mathbb{R}^n$ ,  $n \geq 1$

For a real music signal with  $n$ : huge, we can proceed similarly!

Input signal (say from your mp3 file).

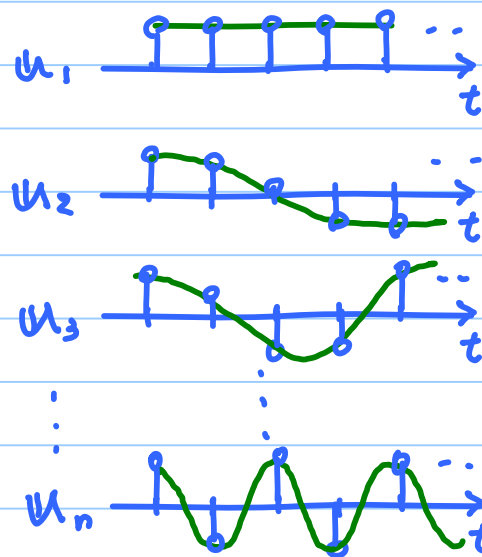
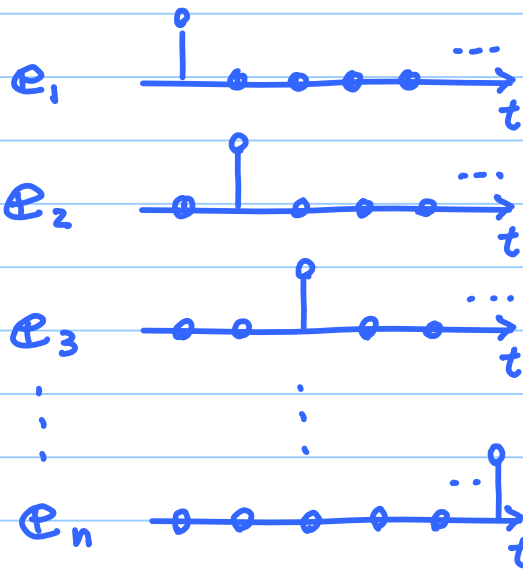


samples form a digital signal

Again, we can write such a digital signal  $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$  as a linear combination of basis vectors.

The basis I

The basis II



$$\mathbf{x} = x_1 \mathbf{e}_1 + \dots + x_n \mathbf{e}_n$$

$$\mathbf{x} = a_1 \mathbf{u}_1 + \dots + a_n \mathbf{u}_n$$

Appropriately choosing the basis  $\{\mathbf{u}_1, \dots, \mathbf{u}_n\}$   
we can **compress** (or more precisely,  
compactly approximate) the input  
signal  $\mathbf{x}$ !

For example, let's use the so-called **Discrete Cosine Transform (DCT)** basis for  $\{u_1, \dots, u_n\}$ .

Then do the following operation:

- (1) Compute the coefficient vector

$$\alpha = [a_1, \dots, a_n]^T.$$

- (2) For  $j = 1:n$ ,

$$\tilde{a}_j := \begin{cases} a_j & \text{if } |a_j| \geq \theta \text{ (a threshold)} \\ 0 & \text{otherwise} \end{cases}$$

- (3) Let  $\tilde{\alpha} := [\tilde{a}_1, \dots, \tilde{a}_n]^T$ , and reconstruct an approximate signal

$$\tilde{x} = U \tilde{\alpha}$$

$$= \tilde{a}_1 u_1 + \dots + \tilde{a}_n u_n$$

**Julia**

$n = 800,791$

$\Rightarrow$  ~~MATLAB~~ Demo with my music signal

- $\theta = 0.1 \Rightarrow$  0.5% of coeff's survived
- $\theta = 0.01 \Rightarrow$  6% of coeff's survived

Also interesting to hear the approximation error  $x - \tilde{x}$  !

If you do the same experiment using  $\{e_1, \dots, e_n\}$  instead of  $\{u_1, \dots, u_n\}$ , you'll hear a huge difference! That is, for a usual music signal, the DCT basis is better than the standard (or canonical) basis  $\{e_1, \dots, e_n\}$ .