

# Maths Preliminaries

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# Introduction

- This review serves two purposes:
  - Recap relevant maths contents that you may have learned a long time ago (probably not in a CS course and rarely used in any CS course).
  - More importantly, present it in a way that is useful (i.e., giving semantics/motivations) for understanding maths behind Machine Learning.
- Contents
  - Linear Algebra

# Note

- You've probably learned Linear Algebra from matrix/system of linear equations, etc. We will review key concepts in LA from the perspective of **linear transformations** (think of it as *functions* for now). This perspective provides **semantics and intuition** into most of the ML models and operations.
  - Here we emphasize more on intuitions; We deliberately skip many concepts and present some contents in an informal way.
- It is a great exercise for you to view related maths and ML models/operations in this perspective *throughout* this course!

# A Common Trick in Maths I

## Question

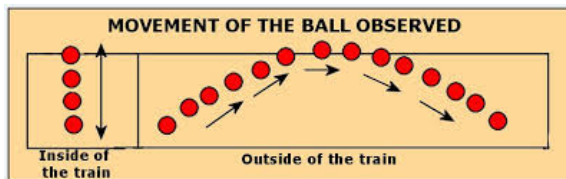
Calculate  $2^{10}$ ,  $2^{-1}$ ,  $2^{\ln 5}$  and  $2^{4-3i}$ ?

- Properties:
  - $f_a(n) = f_a(n-1) * a$ , for  $n \geq 1$ ;  $f_a(0) = 1$ .
  - $f(u) * f(v) = f(u+v)$ .
  - $f(x) = y \Leftrightarrow \ln(y) = x \ln(a) \Leftrightarrow f(x) = \exp\{x \ln a\}$ .
  - $e^{ix} = \cos(x) + i \cdot \sin(x)$ .
- The trick:
- Same in Linear algebra

# Objects and Their Representations

## Goal

- We need to study the objects
- On one side:
  - A good representation helps (a lot)!
- On the other side:
  - Properties of the objects should be independent of the representation!



# Basic Concepts I

## Algebra

- a set of objects
- two operations and their identity objects (aka. *identity element*):
  - addition (+); its identity is **0**.
  - *scalar* multiplication ( $\cdot$ ); its identity is **1**.
- constraints:
  - Closed for both operations
  - Some nice properties of these operations:
    - Commutative:  $\mathbf{a} + \mathbf{b} = \mathbf{b} + \mathbf{a}$ .
    - Associative:  $(\mathbf{a} + \mathbf{b}) + \mathbf{c} = \mathbf{a} + (\mathbf{b} + \mathbf{c})$ .
    - Distributive:  $\lambda(\mathbf{a} + \mathbf{b}) = \lambda\mathbf{a} + \lambda\mathbf{b}$ .

# Basic Concepts II

**Think:** *What about subtraction and division?*

## Tips

Always use analogy from algebra on integers ( $\mathbb{Z}$ ) *and* algebra on Polynomials ( $\mathcal{P}$ ).

Why these constraints are natural and useful?

# Basic Concepts III

## Representation matters?

Consider even geometric vectors:  $\mathbf{c} = \mathbf{a} + \mathbf{b}$

What if we represent vectors by a column of their coordinates?

What if by their polar coordinates? 极坐标

## Notes

- Informally, the objects we are concerned with in this course are (column) vectors.
- The set of all  $n$ -dimensional real vectors is called  $\mathbb{R}^n$ .



# (Column) Vector

3\*4的矩阵为三行四列,

## Vector

- A  $n$ -dimensional vector,  $\mathbf{v}$ , is a  $n \times 1$  matrix. We can emphasize its shape by calling it a *column* vector.
- A *row vector* is a transposed column vector:  $\mathbf{v}^T$ .

## Operations

- Addition:  $\mathbf{v}_1 + \mathbf{v}_2 =$
- (Scalar) Multiplication:  $\lambda \mathbf{v}_1 =$

$n$  linear algebra, a column vector or column matrix is an  $m \times 1$  matrix, that is, a matrix consisting of a single column of  $m$  elements,

列向量就是一个column

行向量就是一个row

列向量的转置矩阵为行向量

行向量的转置矩阵为列向量

# Linearity I

单变量

## Linear Combination: Generalization of Univariate Linear Functions

- Let  $\lambda_i \in \mathbb{R}$ , given a set of  $k$  vectors  $\mathbf{v}_i$  ( $i \in [k]$ ), a linear combination of them is

$$\lambda_1 \mathbf{v}_1 + \lambda_2 \mathbf{v}_2 + \dots + \lambda_k \mathbf{v}_k = \sum_{i \in [k]} \lambda_i \mathbf{v}_i$$

- Later, this is just  $\mathbf{V}\boldsymbol{\lambda}$ , where

$$\mathbf{V} = \begin{bmatrix} | & | & | & | \\ v_1 & v_2 & \dots & v_k \\ | & | & | & | \end{bmatrix} \quad \boldsymbol{\lambda} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \dots \\ \lambda_k \end{bmatrix}$$

- Span: **All** linear combination of a set of vectors is the *span* of them.
- Basis: The **minimal** set of vectors whose span is exactly the whole  $\mathbb{R}^n$ .

# Linearity II

- Benefit: every vector has a **unique** decomposition into basis.

**Think:** *Why uniqueness is desirable?*

## Examples

- Span of  $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$  and  $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$  is  $\mathbb{R}^2$ . They are also the basis.
- Span of  $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ ,  $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ ,  $\begin{bmatrix} 2 \\ 3 \end{bmatrix}$  is  $\mathbb{R}^2$ . But one of them is *redundant*.

**Think:** *Who?*

- Decompose  $\begin{bmatrix} 4 \\ 6 \end{bmatrix}$

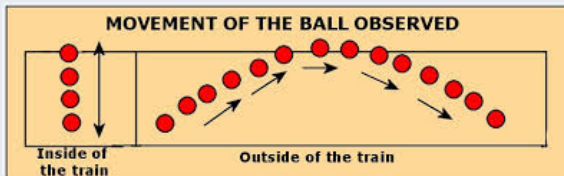
# Linearity III

## Exercises

- What are the (natural) basis of all (univariate) Polynomials of degrees up to  $d$ ?
- Decompose  $3x^2 + 4x - 8$  into *the* linear combination of  $2x - 3$ ,  $x^2 + 1$ .

$$3x^2 + 4x - 7 = 3(x^2 + 1) + 2(2x - 3) + (-2)(2).$$

- The “same” polynomial is mapped to two different vectors under two different bases. **Think:** *Any analogy?* 类推



# Matrix I

## Linear Transformation 线性转换

- is a “nice” linear function that maps a vector in  $\mathbb{R}^n$  to another vector in  $\mathbb{R}^m$ .

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \xrightarrow{f} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

- The general form:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \xrightarrow{f} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \implies \begin{aligned} y_1 &= M_{11}x_1 + M_{12}x_2 \\ y_2 &= M_{21}x_1 + M_{22}x_2 \\ y_3 &= M_{31}x_1 + M_{32}x_2 \end{aligned}$$

# Matrix II

## Nonexample

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \xrightarrow{f} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \implies \begin{aligned} y_1 &= \alpha x_1^2 + \beta x_2 \\ y_2 &= \gamma x_1^2 + \theta x_1 + \tau x_2 \\ y_3 &= \cos(x_1) + e^{x_2} \end{aligned}$$

## Why Only Linear Transformation?

- Simple and nice properties:
  - $(f_1 + f_2)(x) = f_1(x) + f_2(x)$
  - $(\lambda f)(x) = \lambda \cdot f(x)$
  - What about  $f(g(x))$ ?
- Useful



# Matrix I

## Definition

- A  $m \times n$  matrix *corresponds to a linear transformation* from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ 
  - $f(\mathbf{x}) = \mathbf{y} \implies \mathbf{M} \mathbf{x} = \mathbf{y}$ , where matrix-vector multiplication is defined as:  $y_i = \sum_k M_{ik} \cdot x_k$
  - $\mathbf{M}_{\text{outDim} \times \text{inDim}}$
  - *Transformation* or *Mapping* emphasizes more on the mapping between two sets, rather than the detailed specification of the mapping; the latter is more or less the *elementary* understanding of a *function*. These are all specific instances of *morphism* in category theory.

## Semantic Interpretation

# Matrix II

- Linear combination of columns of  $\mathbf{M}$ :

$$\begin{bmatrix} | & | & | & | \\ M_1 & M_2 & \dots & M_n \\ | & | & | & | \end{bmatrix} \begin{bmatrix} | \\ x \\ | \end{bmatrix} = \begin{bmatrix} | & | & | & | \\ M_1 & M_2 & \dots & M_n \\ | & | & | & | \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}$$

## 矩阵乘法

$$\mathbf{y} = x_1 \mathbf{M}_{\bullet 1} + \dots + x_n \mathbf{M}_{\bullet n}$$

- Example:

$$\begin{bmatrix} 1 & 2 \\ -4 & 9 \\ 25 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 10 \end{bmatrix} = 1 \begin{bmatrix} 1 \\ -4 \\ 25 \end{bmatrix} + 10 \begin{bmatrix} 2 \\ 9 \\ 1 \end{bmatrix} = \begin{bmatrix} 21 \\ 86 \\ 35 \end{bmatrix}$$



## Matrix III

## 矩阵乘法

$$\begin{bmatrix} 1 & 2 \\ -4 & 9 \end{bmatrix} \begin{bmatrix} 1 \\ 10 \end{bmatrix} = 1 \begin{bmatrix} 1 \\ -4 \end{bmatrix} + 10 \begin{bmatrix} 2 \\ 9 \end{bmatrix} = \begin{bmatrix} 21 \\ 86 \end{bmatrix}$$

**Think:** What does **M** do for the last example?

- Rotation and scaling
- When **x** is also a matrix,

$$\begin{bmatrix} 1 & 2 \\ -4 & 9 \\ 25 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 10 & 20 \end{bmatrix} = \begin{bmatrix} 21 & 42 \\ 86 & 172 \\ 35 & 70 \end{bmatrix}$$

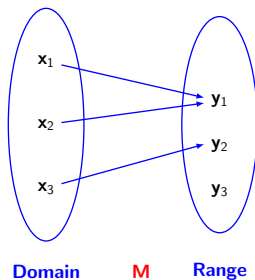
# System of Linear Equations I

## 矩阵乘法

$$\begin{aligned} y_1 &= M_{11}x_1 + M_{12}x_2 \\ y_2 &= M_{21}x_1 + M_{22}x_2 \\ y_3 &= M_{31}x_1 + M_{32}x_2 \end{aligned} \quad \Rightarrow \quad \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \\ M_{31} & M_{32} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$
$$\mathbf{y} = \mathbf{M}\mathbf{x}$$

- Interpretation: find a vector in  $\mathbb{R}^2$  such that its image (under  $\mathbf{M}$ ) is exactly the given vector  $\mathbf{y} \in \mathbb{R}^3$ .
- How to solve it?

# System of Linear Equations II



The above transformation is *injective*, but not *surjective*.

单射

满射

# A Matrix Also Specifies a (Generalized) Coordinate System

I

## Yet another interpretation

- $\mathbf{y} = \mathbf{M}\mathbf{x} \implies \mathbf{I}\mathbf{y} = \mathbf{M}\mathbf{x}$ .
- The vector  $\mathbf{y}$  wrt standard coordinate system,  $\mathbf{I}$ , is the same as  $\mathbf{x}$  wrt the coordinate system defined by **column** vectors of  $\mathbf{M}$ . **Think: why columns of  $\mathbf{M}$ ?**

# A Matrix Also Specifies a (Generalized) Coordinate System II

## Example for polynomials

$$\begin{array}{lcl}
 \text{for } 1 & \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} & \\
 \mathbf{I}: \text{ for } x & & \\
 \text{for } x^2 & & 
 \end{array} \implies \mathbf{M}: \begin{array}{lcl}
 \text{for } 3 & \begin{bmatrix} 3 & -1 & -4 \\ 0 & 1 & 5 \\ 0 & 0 & 2 \end{bmatrix} & \\
 \text{for } x-1 & & \\
 \text{for } 2x^2+5x-4 & & 
 \end{array}$$

$$\text{Let } \mathbf{x} = \begin{bmatrix} 1 \\ -2 \\ 3 \end{bmatrix} \implies \mathbf{M}\mathbf{x} = \mathbf{I} \begin{bmatrix} -7 \\ 13 \\ 6 \end{bmatrix}$$

## Exercise I

- What if  $\mathbf{y}$  is given in the above example?
- What does the following mean?

$$\begin{bmatrix} 3 & -1 & -4 \\ 0 & 1 & 5 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 3 & -1 & -4 \\ 0 & 1 & 5 \\ 0 & 0 & 2 \end{bmatrix}$$

- Think about representing polynomials using the basis:  
 $(x-1)^2$ ,  $x^2-1$ ,  $x^2+1$ .

# Inner Product

## THE binary operator – some kind of “similarity”

- Type signature: vector  $\times$  vector  $\rightarrow$  scalar:  $\langle \mathbf{x}, \mathbf{y} \rangle$ .
  - In  $\mathbb{R}^n$ , usually called *dot product*:  $\mathbf{x} \cdot \mathbf{y} \stackrel{\text{def}}{=} \mathbf{x}^\top \mathbf{y} = \sum_i x_i y_i$ .
  - For certain functions,  $\langle f, g \rangle = \int_a^b f(t)g(t) dt$ .  $\Rightarrow$  leads to the **Hilbert Space**
- Properties / definitions for  $\mathbb{R}$ :
  - conjugate symmetry:  $\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{y}, \mathbf{x} \rangle$
  - linearity in the first argument:  $\langle a\mathbf{x} + \mathbf{y}, \mathbf{z} \rangle = a\langle \mathbf{x}, \mathbf{z} \rangle + \langle \mathbf{y}, \mathbf{z} \rangle$
  - positive definitiveness:  $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$ ;  $\langle \mathbf{x}, \mathbf{x} \rangle \Leftrightarrow \mathbf{x} = \mathbf{0}$ ;
- Generalizes many geometric concepts to vector spaces: angle (orthogonal), projection, norm
  - $\langle \sin nt, \sin mt \rangle = 0$  within  $[-\pi, \pi]$  ( $m \neq n$ )  $\Rightarrow$  they are orthogonal to each other.
- $\mathbf{C} = \mathbf{A}^\top \mathbf{B}$ :  $C_{ij} = \langle A_i, B_j \rangle$ 
  - Special case:  $\mathbf{A}^\top \mathbf{A}$ .

# Eigenvalues/vectors and Eigen Decomposition

“Eigen” means “characteristic of” (German)

- A (right) **eigenvector** of a square matrix  $\mathbf{A}$  is  $\mathbf{u}$  such that  $\mathbf{A}\mathbf{u} = \lambda\mathbf{u}$ .
- Not all matrices have eigenvalues. Here, we only consider “good” matrices. Not all eigenvalues need to be distinct.
- Traditionally, we normalize  $\mathbf{u}$  (such that  $\mathbf{u}^\top \mathbf{u} = 1$ ).
- We can use all eigenvectors of  $\mathbf{A}$  to construct a matrix  $\mathbf{U}$  (as columns). Then  $\mathbf{A}\mathbf{U} = \mathbf{U}\mathbf{\Lambda}$ , or equivalently,  $\mathbf{A} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{-1}$ . This is the **Eigen Decomposition**.
  - We can interpret  $\mathbf{U}$  as a transformation between two coordinate systems. **Note** that vectors in  $\mathbf{U}$  are not necessarily orthogonal.
  - $\mathbf{\Lambda}$  as the scaling on each of the directions in the “new” coordinate system.



# Similar Matrices

## Similar Matrix

- Let  $\mathbf{A}$  and  $\mathbf{B}$  be two  $n \times n$  matrix.  $\mathbf{A}$  is **similar** to  $\mathbf{B}$  (denoted as  $\mathbf{A} \sim \mathbf{B}$ ) if there exists an invertible  $n \times n$  matrix  $\mathbf{P}$  such that  $\mathbf{P}^{-1}\mathbf{A}\mathbf{P} = \mathbf{B}$ .
- **Think:** *What does this mean?*
  - Think of  $\mathbf{P}$  as a *change of basis* transformation.
  - Relationship with the Eigen decomposition.
- Similar matrices have the same value wrt many properties (e.g., rank, trace, eigenvalues, determinant, etc.)

## SVD

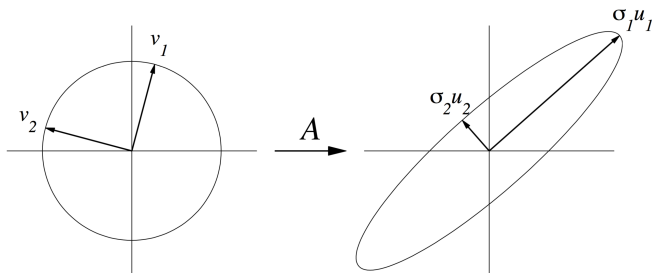
## Singular Vector Decomposition

- Let  $\mathbf{M}$  be  $n \times d$  ( $n \geq d$ ).
- Reduced SVD:  $\mathbf{M} = \hat{\mathbf{U}} \hat{\Sigma} \mathbf{V}^\top$  exists for any  $\mathbf{M}$ , such that
  - $\hat{\Sigma}$  is a diagonal matrix with diagonal elements  $\sigma_i$  (called *singular values*) in decreasing order
  - $\hat{\mathbf{U}}$  consists of an (incomplete) set of basis vectors  $\mathbf{u}_i$  (*left singular vectors* in  $\mathbb{R}^n$ ) ( $n \times d$ : original space as  $\mathbf{M}$ )
  - $\hat{\mathbf{V}}$  consists of a set of basis vectors  $\mathbf{v}_i$  (*right singular vectors* in  $\mathbb{R}^d$ ) ( $d \times d$ : reduced space)
- Full SVD:  $\mathbf{M} = \mathbf{U} \Sigma \mathbf{V}^\top$ :
  - Add the remaining  $(n - d)$  basis vectors to  $\hat{\mathbf{U}}$  (thus becomes  $n \times n$ ).
  - Add the  $n - d$  rows of  $\mathbf{0}$  to  $\hat{\Sigma}$  (thus becomes  $n \times d$ ).

# Geometric Illustration of SVD

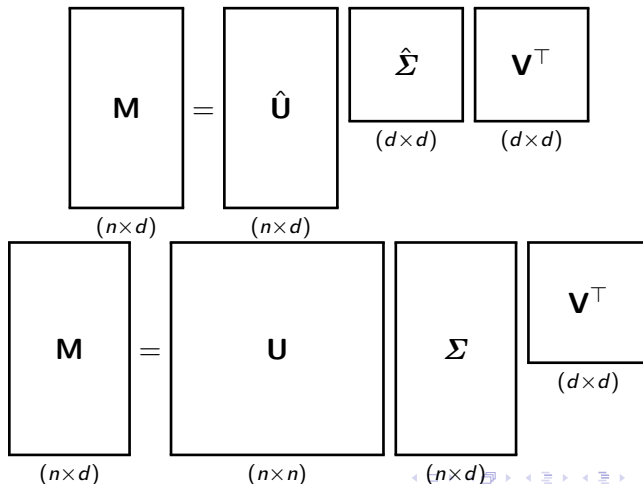
## Geometric Meaning

- $Mv_i = \sigma_i u_i$



# Graphical Illustration of SVD I

Figure: Reduced SVD vs Full SVD



# Graphical Illustration of SVD II

Meaning:

- Columns of  $\mathbf{U}$  are the basis of  $\mathbb{R}^n$
- Rows of  $\mathbf{V}^T$  are the basis of  $\mathbb{R}^d$

# SVD Applications I

## Relationship between Singular Values and Eigenvalues

- What are the eigenvalues of  $\mathbf{M}^\top \mathbf{M}$ ?
- Hint:  $\mathbf{M} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^\top$  and  $\mathbf{U}$  and  $\mathbf{V}$  are unitary (i.e., rotations)

- Related to *PCA (Principle Component Analysis)*

# References and Further Reading I

- Gaussian Quadrature:  
<https://www.youtube.com/watch?v=k-yUdqRXijo>
- Linear Algebra Review and Reference.  
<http://cs229.stanford.edu/section/cs229-linalg.pdf>
- Scipy LA tutorial. <https://docs.scipy.org/doc/scipy/reference/tutorial/linalg.html>
- We Recommend a Singular Value Decomposition.  
<http://www.ams.org/samplings/feature-column/fcarc-svd>