Maths Preliminaries

- 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 probability 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

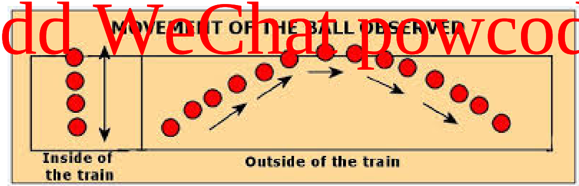
Calculate 2^{10}, 2^{-1}, $2^{\ln 5}$ and 2^{4-3i}?

- 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!



Algebra

- a set of objects
- two operations and their identity objects (aka. *identify element*):
  - addition (+); its identity is 0.
  - *scalar* multiplication ($\cdot$); its identity is 1.

- constraints:
  - Closed for both operations.
  - Some nice properties of these operations:
    - Communicative: $a + b = b + a$.
    - Associative: $(a + b) + c = a + (b + c)$.
    - Distributive: $\lambda(a + b) = \lambda a + \lambda b$.

Think: *What about substraction 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: c = a + b

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

What if by their polar coordinates?

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

Vector

- A n-dimensional vector, 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: $\mathrm{v}^\top$.

Operations

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

Linear Combination: Generalization of Univariate Linear Functions

- Let $\lambda_i \in \mathbb{R}$, given a set of k vectors v_i ($i \in [k]$), a linear combination of them is
  $\lambda_1 \mathsf{v}_1 + \lambda_2 \mathsf{v}_2 + \ldots + \lambda_k \mathsf{v}_k = \sum_{i \in [k]} \lambda_i \mathsf{v}_i$
    - Later, this is just $\mathsf{V}\boldsymbol{\lambda}$, where

$$\mathsf{V} = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \ldots & v_k \\ | & | & & | \end{bmatrix} \qquad \lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \ldots \\ \lambda_k \end{bmatrix}$$

- 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 $\mathbb{R}^n$.

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

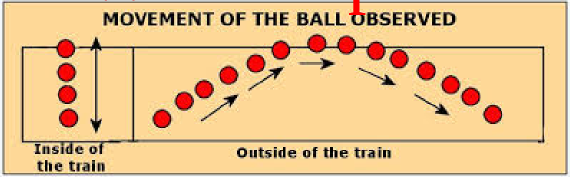
Exercises

- What are the (natural) basis of all (univariate) Polynomials of degrees up to d?

- Decompose $3x^2 + 4x - 7$ into *the* linear combination of 2, $2x - 3$, $x^2 + 1$.

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

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



Linear Transformation

- 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:

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

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

Definition

- A $m \times n$ matrix *corresponds to* a *linear transformation* from $\mathbb{R}^n$ to $\mathbb{R}^m$
  - $f(\mathrm{x}) = \mathrm{y} \implies \mathrm{M}\,\mathrm{x} = \mathrm{y}$, where matrix-vector multiplication is defined as: $y_i = \sum_k M_{ik} \cdot x_k$
  - $\mathrm{M}_{\mathrm{outDim} \times \mathrm{inDim}}$
  - *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 M:

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

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

- Example:

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

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

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

- Rotation and scaling

- When x is also a matrix,

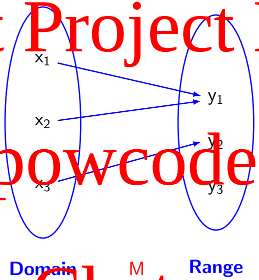
$$\begin{bmatrix} 1 & 2 \\ -4 & 9 \\ 25 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 10 & 20 \end{bmatrix} = \begin{bmatrix} 21 & 42 \\ 86 & 172 \\ 35 & 70 \end{bmatrix}$$

System of Linear Equations I

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

$$\mathrm{y} = \mathrm{Mx}$$

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



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

A Matrix Also Specifies a (Generalized) Coordinate System I

Yet another interpretation

- $y = Mx \implies Iy = Mx$
- The vector y wrt standard coordinate system, I, is the same as x wrt the coordinate system defined by column vectors of M.

$\boxed{\textbf{Think: } \textit{why columns of M?}}$

Example for polynomials

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

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

- What if 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 $\to$ scalar: $\langle \mathrm{x}, \mathrm{y} \rangle$.
  - In $\mathbb{R}^n$, usually called *dot product*: $\mathrm{x} \cdot \mathrm{y} \stackrel{\text{def}}{=} \mathrm{x}^\top \mathrm{y} = \sum_i x_i y_i$.
  - For certain functions, $\langle f, g \rangle = \int_a^b f(t)g(t)\,\mathrm{d}t$. $\Rightarrow$ leads to the Hilbert Space
- Properties / definitions for $\mathbb{R}$:
  - conjugate symmetry: $\langle \mathrm{x}, \mathrm{y} \rangle = \langle \mathrm{y}, \mathrm{x} \rangle$
  - linearity in the first argument: $\langle a\mathrm{x} + \mathrm{y}, \mathrm{z} \rangle = a\langle \mathrm{x}, \mathrm{z} \rangle + \langle \mathrm{y}, \mathrm{z} \rangle$
  - positive definitiveness: $\langle \mathrm{x}, \mathrm{x} \rangle \geq 0$; $\langle \mathrm{x}, \mathrm{x} \rangle \Leftrightarrow \mathrm{x} = 0$;
- 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.
- $\mathrm{C} = \mathrm{A}^\top \mathrm{B}$: $C_{ij} = \langle A_i, B_j \rangle$
  - Special case: $\mathrm{A}^\top \mathrm{A}$.

"Eigen" means "characteristic of" (German)

- A (right) eigenvector of a square matrix A is u such that $Au = \lambda u$.
- Not all matrices have eigenvalues. Here, we only consider "good" matrices. Not all eigenvalues need to be distinct.

- Traditionally, we normalize u (such that $u^\top u = 1$).
- We can use all eigenvectors of A to construct a matrix U (as columns). Then $AU = U\Lambda$, or equivalently, $A = U\Lambda U^{-1}$. This is the Eigen Decomposition.

  - We can interpret U as a transformation between two coordinate systems. Note that vectors in U are not necessarily orthogonal.
  - Λ as the scaling on each of the directions in the "new" coordinate system.

Similar Matrix

- Let A and B be two $n \times n$ matrix. A is similar to B (denoted as $A \sim B$) if there exists an invertible $n \times n$ matrix P such that $P^{-1}AP = B$.

- $\boxed{\textbf{Think:} \textit{ What does this mean?}}$
  - Think of P as a *change of basis* transformation.
  - Relationship with the Eigen decomposition.

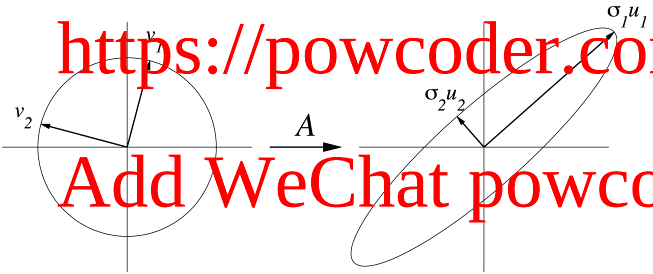
- Similar matrices have the same value wrt many properties (e.g., rank, trace, eigenvalues, determinant, etc.)

Singular Vector Decomposition

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

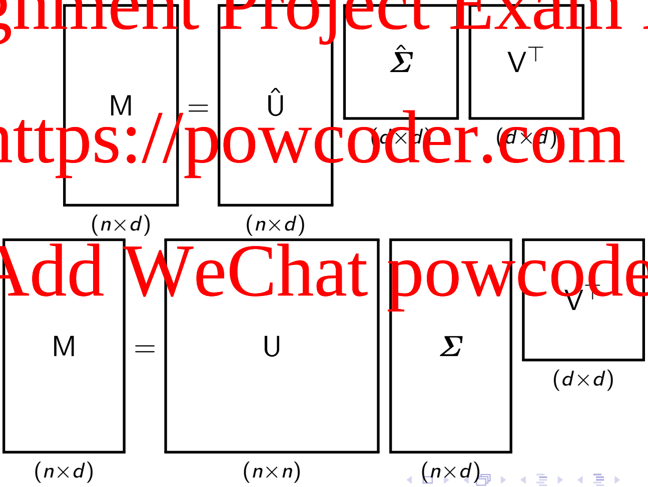
Geometric Meaning

- $Mv_i = \sigma_i u_i$



Graphical Illustration of SVD I

Figure: Reduced SVD vs Full SVD



Meaning:

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

Relationship between Singular Values and Eigenvalues

- What are the eigenvalues of $M^\top M$?
- Hint: $M = U\Sigma V^\top$ and U and 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