計算科学における情報圧縮

Information Compression in Computational Science

2017.10.12

#3:情報圧縮の数理1 （線形代数の復習）

Review of linear algebra

理学系研究科　物理学専攻　大久保　毅

Department of Physics, **Tsuyoshi Okubo**

Outline

- Vector space- Abstract vectors-
  - Geometric vectors
  - General vector space (with inner product)
  - Basis and relation to coordinate vector space
- Matrix and linear map
  - Relation between matrices and linear maps
  - Important properties and operations for matrices
- Eigenvalue problem and diagonalization

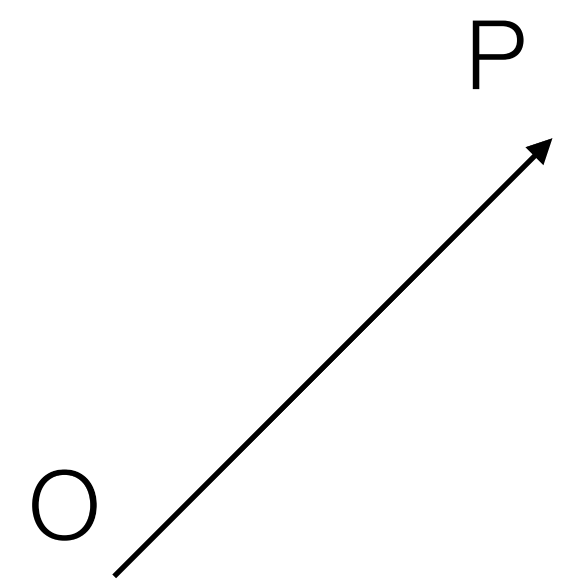
Vector space -Abstract vectors-

Geometric vector

Geometric vector: Arrow on the plane (or the space) ,

which has "Direction" and "Length"

$$\vec{v} \equiv \overrightarrow{OP}$$



We can express a vector by its component:

$$\vec{v} = \begin{pmatrix} v_x \\ v_y \\ v_z \end{pmatrix} = \begin{pmatrix} x_p - x_o \\ y_p - y_o \\ z_p - z_o \end{pmatrix}$$

Properties of vector

Properties of addition:

$$\vec{a}+\vec{b}=\vec{b}+\vec{a}$$

Commutative property（交換法則）

$$\left(\vec{a}+\vec{b}\right)+\vec{c}=\vec{a}+\left(\vec{b}+\vec{c}\right)$$

Associative property（結合法則）

$$\vec{a}+\vec{0}=\vec{a}$$

zero vector

$$\vec{a}+(-\vec{a})=\vec{0}$$

inverse vector

Multiplication of scaler $c \in \boldsymbol{R}$（実数）：

$$c(\vec{a}+\vec{b})=c\vec{b}+c\vec{a}$$

$$(c+d)\vec{a}=c\vec{a}+d\vec{a}$$

$$(cd)\vec{a}=c\,(d\vec{a})$$

Distributive property（分配法則）

Inner product of vector

Inner product:

$$(\vec{a}, \vec{b}) \equiv \vec{a} \cdot \vec{b}$$

$$= a_x b_x + a_y b_y + a_z b_z$$

Example:

$$\vec{a} = \begin{pmatrix} a_x \\ a_y \\ a_z \end{pmatrix}, \vec{b} = \begin{pmatrix} b_x \\ b_y \\ b_z \end{pmatrix}$$

Properties:

$$(\vec{a}, \vec{a}) \geq 0$$

$$(\vec{a}, \vec{b}) = (\vec{b}, \vec{a})$$

$$(\vec{a} + \vec{b}, \vec{c}) = (\vec{a}, \vec{c}) + (\vec{b}, \vec{c})$$

$$(c\vec{a}, \vec{b}) = c(\vec{a}, \vec{b}) \qquad c \in \boldsymbol{R}$$

Norm (length):

$$\|\vec{a}\| \equiv \sqrt{(\vec{a}, \vec{a})}$$

Vector space (linear space)

Vector space $\boldsymbol{V}$: generalization of geometric vector

Set of elements (vectors) satisfying following **axioms**（公理）

Properties of addition:

$$\vec{a}+\vec{b}=\vec{b}+\vec{a}$$ Commutative property（交換法則）

$$\left(\vec{a}+\vec{b}\right)+\vec{c}=\vec{a}+\left(\vec{b}+\vec{c}\right)$$ Associative property（結合法則）

$$\vec{a}+\vec{0}=\vec{a}$$ Existence of unique zero vector

$$\vec{a}+(-\vec{a})=\vec{0}$$ Existence of unique inverse vector

Multiplication of scaler c :

$$c(\vec{a}+\vec{b})=c\vec{b}+c\vec{a}$$

$$(c+d)\vec{a}=c\vec{a}+d\vec{a}$$

$$(cd)\vec{a}=c\,(d\vec{a})$$

$c\in\boldsymbol{R}$: Real vector space

$c\in\boldsymbol{C}$: Complex vector space

Inner product space (metric vector space)

（計量空間）

Inner product space:

Vector space + definition of inner product

Inner product: $(\vec{a}, \vec{b})$

Axiom:

$$(\vec{a}, \vec{a}) \geq 0$$

$$(\vec{a}, \vec{b}) = (\vec{b}, \vec{a})^*$$

$$(\vec{a} + \vec{b}, \vec{c}) = (\vec{a}, \vec{c}) + (\vec{b}, \vec{c})$$

$$(c\vec{a}, \vec{b}) = c(\vec{a}, \vec{b})$$

*If a norm defined from the inner product is "complete"（完備）,

that space is called **Hilbert space**.

Examples of vector spaces

(1) Coordinate space（数ベクトル空間） $\boldsymbol{R}^n, \boldsymbol{C}^n$

Vector: $$\vec{v} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix} \quad v_i \in \boldsymbol{R} \text{ or } \boldsymbol{C}$$

Inner product: $$(\vec{a}, \vec{b}) \equiv \vec{a} \cdot \vec{b}^*$$

(2) Wave vectors in quantum physics

Vector: $$|\Psi\rangle$$

Inner product: $$(|a\rangle, |b\rangle) = \langle b|a\rangle$$

Linearly independent or dependent

（線形独立） （線形従属）

Linear combination:

$$\vec{x} = c_1\vec{v}_1 + c_2\vec{v}_2 + \cdots c_k\vec{v}_k$$

$$\vec{v}_i \in \boldsymbol{V} \qquad c_i \in \boldsymbol{R} \text{ or } \boldsymbol{C}$$

A set $\{\vec{v}_1, \vec{v}_2, \cdots \vec{v}_k\}$ is **linearly independent** when

$\vec{x} = \vec{0}$ is satisfied if and only if $c_1 = c_2 = \cdots = c_k = 0$

$$\Updownarrow$$

A set $\{\vec{v}_1, \vec{v}_2, \cdots \vec{v}_k\}$ is **linearly dependent** when

it is not linearly independent.

Basis of vector space
（基底）

A set $\{\vec{e}_1, \vec{e}_2, \cdots \vec{e}_n\}$ $(\vec{e}_i \in \boldsymbol{V})$ is a basis（基底）of $\boldsymbol{V}$ when

$\{\vec{e}_1, \vec{e}_2, \cdots \vec{e}_n\}$ is linearly independent.

and

Any vectors in $\boldsymbol{V}$ are represented by its linear combination.

$\vec{e}_i$: basis vector

# of basis vectors (n) is called **dimension** （次元）of $\boldsymbol{V}$.

$$n = \mathrm{dim}\boldsymbol{V}$$

Relation (map) to coordinate vector space

By using a basis $\{\vec{e}_1, \vec{e}_2, \cdots \vec{e}_n\}$, $\vec{v} \in \boldsymbol{V}$ is uniquely represented as

(* From linear independency)

$$\vec{v} = v_1\vec{e}_1 + v_2\vec{e}_2 + \cdots v_n\vec{e}_n$$

We can represent $\vec{v}$ as a coordinate vector

$$\vec{v} \to \begin{pmatrix} v_1 \\ v_2 \\ \cdots \\ v_n \end{pmatrix} \in \boldsymbol{C}^n (\text{ or } \boldsymbol{R}^n)$$

By selecting a basis, we obtain a "concrete" coordinate vector for an "abstract" vector

Orthonormal basis （正規直交基底）

When a vector space has an inner product,

$\vec{a}, \vec{b}$ is **orthogonal** （直交） if $(\vec{a}, \vec{b}) = 0$.

Orthonormal basis

A basis $\{\vec{e}_1, \vec{e}_2, \cdots \vec{e}_n\}$ is an orthonormal basis when

$$\|\vec{e}_i\| = 1 \qquad (i = 1, 2, \ldots, n)$$

$$(\vec{e}_i, \vec{e}_j) = 0 \qquad (i \neq j; i, j = 1, 2, \ldots, n)$$

*A basis can be transformed into an orthonormal basis.

cf. Gram-Schmidt orthonormalization

Vector subspace (linear subspace)

Vector subspace:

A subset $\boldsymbol{W}$ of a vector space $\boldsymbol{V}$ is a vector subspace of $\boldsymbol{V}$ when $\boldsymbol{W}$ satisfies the same axioms of vector space with $\boldsymbol{V}$.

The following conditions are necessary and sufficient.

$$\vec{a}, \vec{b} \in \boldsymbol{W} \Rightarrow \vec{a} + \vec{b} \in \boldsymbol{W}$$

$$\vec{a} \in \boldsymbol{W}, c \in \boldsymbol{C} \Rightarrow c\vec{a} \in \boldsymbol{W}$$

(In the case of complex vector space)

Spanned vector subspace

Spanned subspace:

For a subset $\boldsymbol{S}$ of a vector space $\boldsymbol{V}$, a set of linear combinations

$$\{c_1\vec{s}_1 + c_2\vec{s}_2 \cdots + c_k\vec{s}_k | c_i \in \boldsymbol{C}, \vec{s}_i \in \boldsymbol{S}\}$$

becomes a vector subspace of $\boldsymbol{V}$.

We often use

$$\mathrm{Span}\{\vec{s}_1, \vec{s}_2, \cdots, \vec{s}_k\}$$

to represents a vector subspace spanned by a set of vectors

$$\{\vec{s}_1, \vec{s}_2, \cdots, \vec{s}_k\}$$

(This representation may appear in Krylov subspace method)

Matrix and linear map

Matrix（行列）

Matrix: "Table" of (complex) numbers in a rectangular form

M × N matrix

$$A = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1,N} \\ A_{21} & A_{22} & \cdots & A_{2,N} \\ \vdots & \vdots & & \vdots \\ A_{M1} & A_{M2} & \cdots & A_{M,N} \end{pmatrix}$$

$$A_{ij} \in \boldsymbol{C}(\text{ or } \boldsymbol{R})$$

Product of matrices: $C = AB$

$$C_{ij} = \sum_{k=1}^{K} A_{ik} B_{kj}$$

$A : M \times K$

$B : K \times N$

$C : M \times N$

In general: $XY \neq YX$

*We also know addition, multiplication of scalar.

Identity matrix（単位行列）

Identity matrix:

N × N matrix
(Square matrix)

$$I = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

Product:

$$IA = A \qquad A : N \times M$$

$$BI = B \qquad B : K \times N$$

* Element of the identity matrix: $I_{ij} = \delta_{ij}$ (Kronecker delta)

$$\delta_{ij} = \begin{cases} 1 & (i = j) \\ 0 & (i \neq j) \end{cases}$$

Transpose, complex conjugate and adjoint

Transpose:
(転置)

$$A^t \qquad (A^t)_{ij} = A_{ji}$$

Complex conjugate:
(複素共役)

$$A^* \qquad (A^*)_{ij} = A^*_{ij}$$

Adjoint:
(随伴)
or
Hermitian conjugate:
(エルミート共役)

$$A^\dagger = (A^t)^* = (A^*)^t$$

$$(A^\dagger)_{ij} = A^*_{ji}$$

("Dagger" is convention in physics)

Multiplication to coordinate vector

$$A : M \times N \qquad \vec{v} \in \boldsymbol{C}^N \qquad \vec{v}' \in \boldsymbol{C}^M$$

$$\begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1,N} \\ A_{21} & A_{22} & \cdots & A_{2,N} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ A_{M1} & A_{M2} & \cdots & A_{M,N} \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_N \end{pmatrix} = \begin{pmatrix} v'_1 \\ v'_2 \\ \vdots \\ \vdots \\ v'_M \end{pmatrix}$$

M × N matrix transforms a N-dimensional coordinate vector to a M-dimensional coordinate vector.

M × N matrix ⟷ **Linear map:** $C^N \to C^M$

1 to 1 （線形写像）

General linear map

Map: $f : \boldsymbol{V} \to \boldsymbol{V}'$

$$f(\vec{v}) = \vec{v}' \qquad (\vec{v} \in \boldsymbol{V}, \vec{v}' \in \boldsymbol{V}')$$

Linear map:

$$f(\vec{x} + \vec{y}) = f(\vec{x}) + f(\vec{y})$$

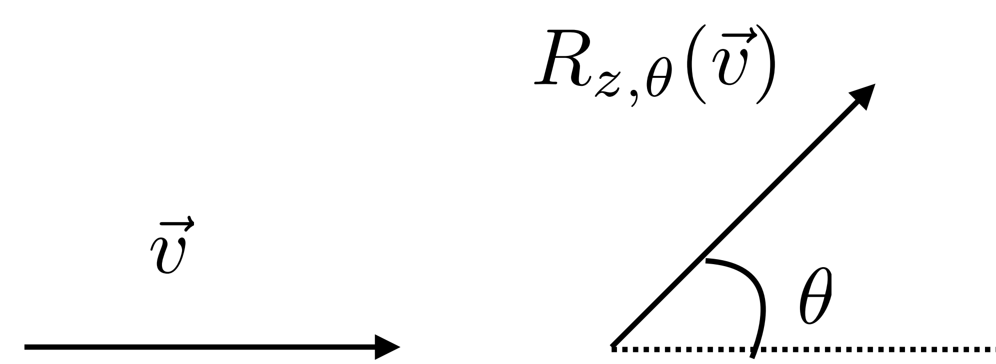
$$f(c\vec{x}) = cf(\vec{x})$$

$$(\vec{x}, \vec{y} \in \boldsymbol{V}, c \in \boldsymbol{C})$$

Examples:

Rotation (e.g. θ rotation around z-axis)

$$R_{z,\theta} : \boldsymbol{C}^3 \to \boldsymbol{C}^3$$



Hamiltonian operator

$$\mathcal{H} : \boldsymbol{V} \to \boldsymbol{V}$$

$$|\Psi\rangle \rightarrow \mathcal{H}|\Psi\rangle$$

Matrix representation of linear map

By using a basis, we can represent a linear map in a matrix.

$$f : \boldsymbol{V} \to \boldsymbol{V}'$$

Vector space $\boldsymbol{V} : \dim \boldsymbol{V} = N$ $\Rightarrow$ $\boldsymbol{V}' : \dim \boldsymbol{V}' = M$

Basis $\{\vec{e}_1, \vec{e}_2, \cdots, \vec{e}_N\}$ $\quad$ $\{\vec{e'}_1, \vec{e'}_2, \cdots, \vec{e'}_M\}$

Transformation of basis vectors:

$$f(\vec{e}_j) = f_{1j}\vec{e'}_1 + f_{2j}\vec{e'}_2 + \cdots + f_{Mj}\vec{e'}_M$$

$\Rightarrow$ $f : \boldsymbol{V} \to \boldsymbol{V}'$ $\Leftrightarrow$ $\begin{pmatrix} f_{11} & f_{12} & \cdots & f_{1,N} \\ f_{21} & f_{22} & \cdots & f_{2,N} \\ \vdots & \vdots & & \vdots \\ f_{M1} & f_{M2} & \cdots & f_{M,N} \end{pmatrix}$

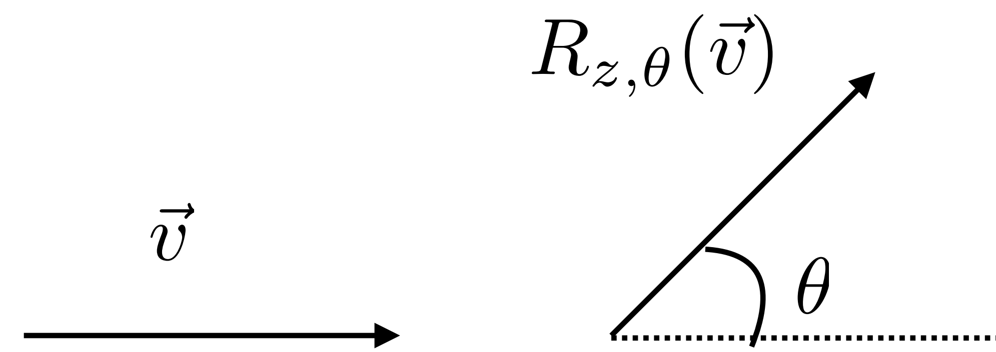
1 to 1

(if we fix basis)

Examples of matrix

Rotation (e.g. θ rotation around z-axis)

$$R_{z,\theta} : \boldsymbol{C}^3 \to \boldsymbol{C}^3$$



$$R_{z,\theta} = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Hamiltonian operator

$$\mathcal{H} : \boldsymbol{V} \to \boldsymbol{V}$$

$$\mathcal{H} \to \begin{pmatrix} H_{0,0;0,0} & H_{0,0;0,1} & H_{0,0;1,0} & H_{0,0;1,1} \\ H_{0,1;0,0} & H_{0,1;0,1} & H_{0,1;1,0} & H_{0,1;1,1} \\ H_{1,0;0,0} & H_{1,0;0,1} & H_{1,0;1,0} & H_{1,0;1,1} \\ H_{1,1;0,0} & H_{1,1;0,1} & H_{1,1;1,0} & H_{1,1;1,1} \end{pmatrix}$$

Matrix element:
(行列要素)

$$H_{\alpha,\beta;\alpha',\beta'} \equiv \langle \alpha\beta | \mathcal{H} | \alpha'\beta' \rangle$$

* In this notation, basis should be orthonormal.

Image of a map

$f : \boldsymbol{V} \to \boldsymbol{V}'$

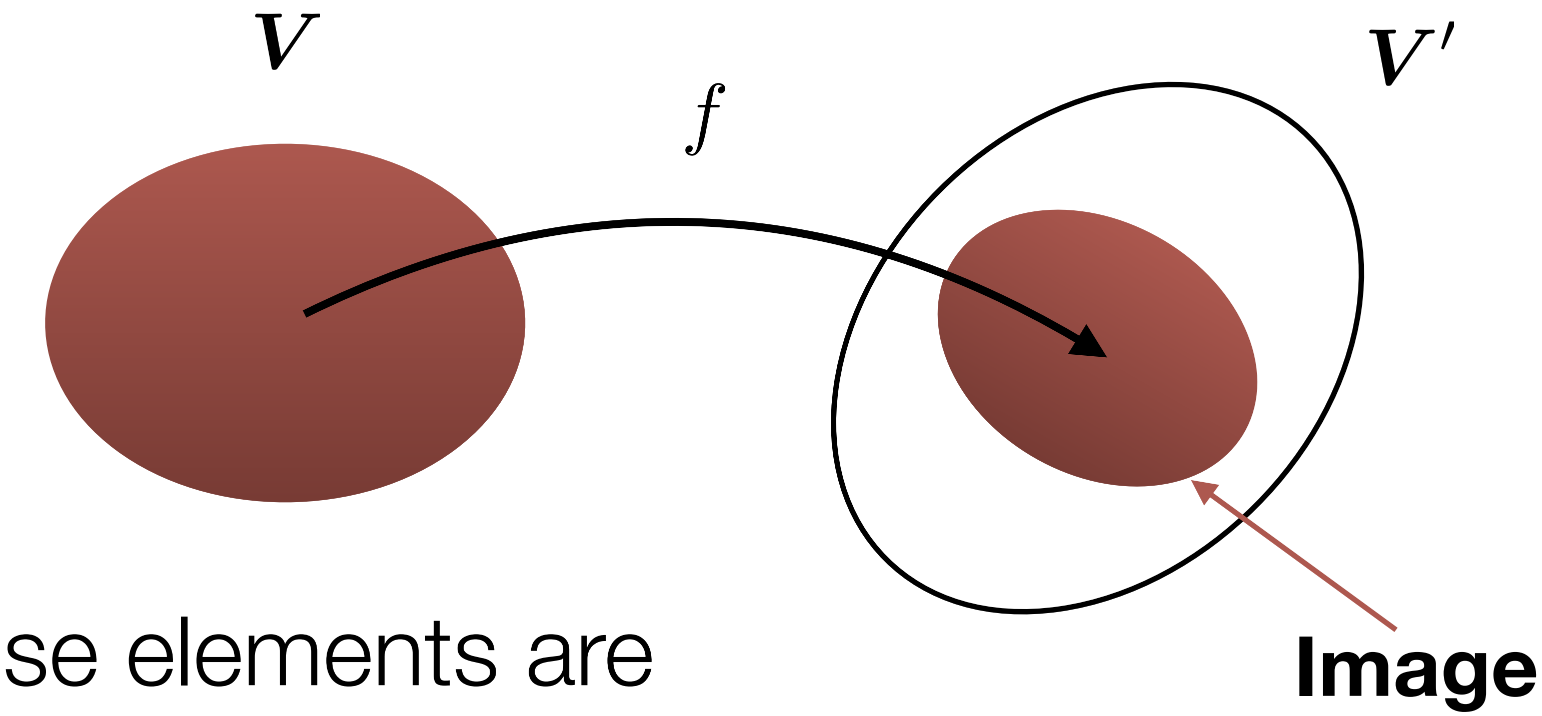


Image of f:
（像）

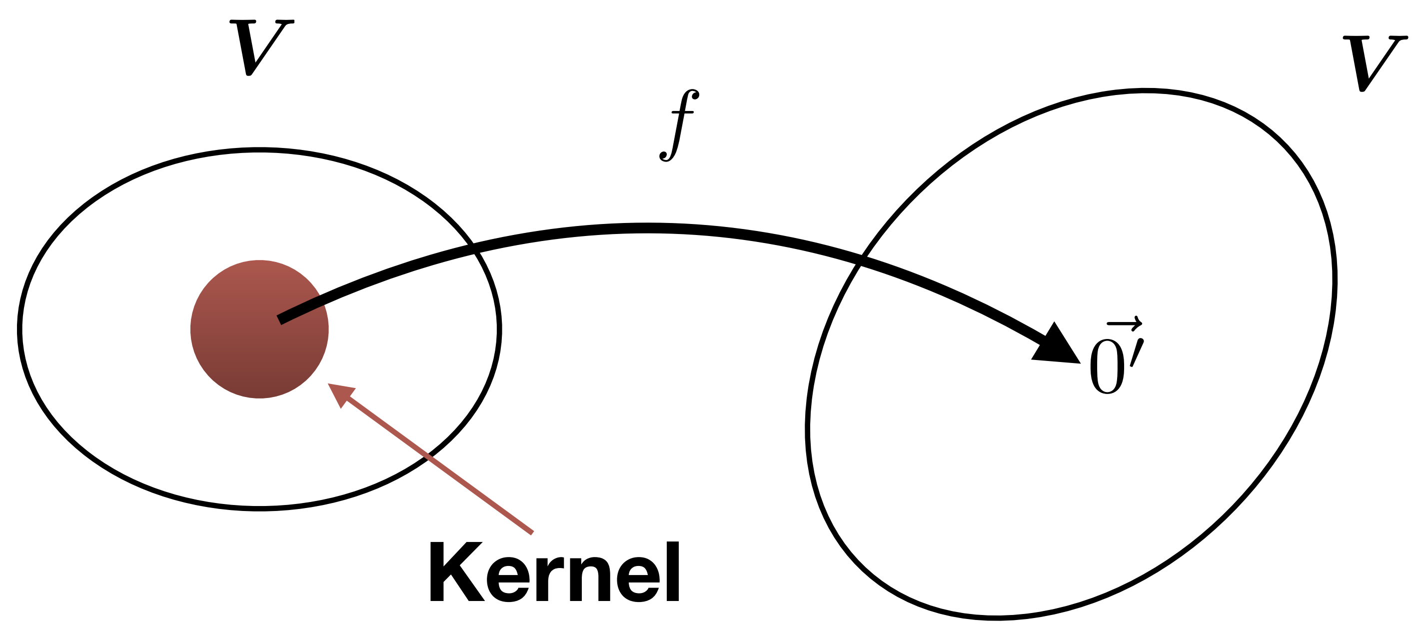
Vector subspace whose elements are mapped from $\boldsymbol{V}$ by f.

$$\mathrm{img}(f) = \{\vec{v}' | \vec{v} \in \boldsymbol{V}, \vec{v}' = f(\vec{v})\}$$

Kernel of a map

$f : \boldsymbol{V} \rightarrow \boldsymbol{V}'$

Kernel of f:
(核)



Vector subspace whose elements are mapped into zero vector by f .

$$\ker(f) = \{\vec{v} | \vec{v} \in \boldsymbol{V}, f(\vec{v}) = \vec{0}'\}$$

Theorem:

$$\dim(V) = \dim(\ker(f)) + \dim(\mathrm{img}(f))$$

Rank of matrix

Rank （ランク or 階数）of a matrix *A*:

$$\mathrm{rank}(A) \equiv \dim(\mathrm{img}(A))$$

Rank is identical with

Maximum # of linearly independent column vectors （列ベクトル）in *A*

Maximum # of linearly independent row vectors （行ベクトル）in *A*

$$\mathrm{rank}(A) \leq \min(M, N)$$

for a *N*×*M* matrix *A.*

$$\begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1,N} \\ A_{21} & A_{22} & \cdots & A_{2,N} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ A_{M1} & A_{M2} & \cdots & A_{M,N} \end{pmatrix}$$

Regular matrix and its inverse matrix

A square matrix A is a **regular matrix** （正則）if a matrix X satisfying

$$AX = XA = I$$

exists. The matrix X is called inverse matrix（逆行列） of A and it is written as $X = A^{-1}$.

Properties: A^{-1} is unique.

$$(A^{-1})^{-1} = A$$

$$(AB)^{-1} = B^{-1}A^{-1}$$

A is a regular matrix $\Leftrightarrow$ $\mathrm{rank}(A) = N$

Can we consider an "inverse matrix" of a non-regular matrix (including a rectangular matrix) ?

$\Rightarrow$ Next week!

Simultaneous linear equation

Simultaneous linear equation（連立一次方程式）

can be represented by a matrix and a vector as

$$A\vec{x} = \vec{b} \qquad A : M \times N, \vec{x} \in \boldsymbol{C}^N, \vec{b} \in \boldsymbol{C}^M$$

If A is a square matrix (*N*=*M*), and it has a inverse matrix (rank(A) =N),
we can solve the equation as

$$\vec{x} = A^{-1}\vec{b}$$

How can we find a "solution" when A does not have a "inverse"?

→ It is probably related to the topic "sparse modeling".

Determinant of matrix

For a square matrix *A* its **determinant**（行列式） is defined as

$$\det A = |A| = \sum_{\sigma} \mathrm{sgn}(\sigma) A_{1\sigma(1)} A_{2\sigma(2)} \cdots A_{N\sigma(N)}$$
$$= \sum_{\sigma} \mathrm{sgn}(\sigma) A_{\sigma(1)1} A_{\sigma(2)2} \cdots A_{\sigma(N)N}$$

σ :permutation（置換） of {1,2,...,N}

$$\sigma = \begin{cases} 1 & \text{even permutation} \\ -1 & \text{odd permutation} \end{cases}$$
（偶置換）
（奇置換）

Examples:

$$\begin{vmatrix} a & b \\ c & d \end{vmatrix} = ab - cd$$

$$\begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} = aei + bfg + cdh \\ -afg - bdi - ceg$$

Determinant and inverse matrix

By using the determinant of *A*, we can represent its inverse matrix:

$$A^{-1} = \frac{1}{\det(A)} \begin{pmatrix} \tilde{A}_{11} & \tilde{A}_{21} & \cdots & \tilde{A}_{N1} \\ \tilde{A}_{12} & \tilde{A}_{22} & \cdots & \tilde{A}_{N2} \\ \vdots & \vdots & & \vdots \\ \tilde{A}_{1N} & \tilde{A}_{2N} & \cdots & \tilde{A}_{NN} \end{pmatrix}$$

$\tilde{A}_{ij}$:cofactor（余因子）

We can see that

$\det(A) = 0$ ⇒ A^{-1} diverges

Indeed,

A is a regular matrix. ⇔ $\det(A) \neq 0$

necessary and sufficient

Eigenvalue problems and diagonalization

Eigenvalue and Eigenvector

For a square matrix A

$$A\vec{v} = \lambda\vec{v}$$

$\vec{v} \neq \vec{0}$:eigenvector（固有ベクトル）

$\lambda \in \boldsymbol{C}$:eigenvalue（固有値）

Properties:

If $\vec{v}$ is an eigenvector, $c\vec{v}$ is also an eigenvector.

Eigenspace（固有空間）：

The set of eigenvectors corresponds an eigenvalue λ.

Eigenvectors corresponding to different eigenvalues are linearly independent.

Right and left eigenvectors

In general, left eigenvectors can be different from the right eigenvectors.

$$A\vec{v} = \lambda\vec{v}$$

$$(\vec{u}^*)^t A = \lambda(\vec{u}^*)^t$$

$\vec{v}$:Right eigenvector

$(\vec{u}^*)^t$:Left eigenvector

Properties:

Set of eigenvalues are identical between the right and the left eigenvectors.

A left eigenvector and a right eigenvector are orthogonal when they correspond to different eigenvalues.

$$\vec{u}_i^* \cdot \vec{v}_j = 0 \qquad (\lambda_i \neq \lambda_j)$$

Diagonalization

Diagonalizaiton（対角化）：

$$A : N \times N$$

$$P^{-1}AP = \begin{pmatrix} \alpha_1 & & & \\ & \alpha_2 & & \\ & & \ddots & \\ & & & \alpha_N \end{pmatrix}$$

A can be diagonalized. ⟺ A has N linearly independent eigenvectors.

necessary and sufficient

$$\alpha_i = \lambda_i$$

$$P = (\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_N)$$

$$(P^{-1})^t = (\vec{u}_1^*, \vec{u}_2^*, \cdots, \vec{u}_N^*)$$

Normalization: $\vec{u}_i^* \cdot \vec{v} = 1$

Meaning of diagonalization

General transform using a regular matrix: $P^{-1}AP$

It is a transform of the basis:

$$\{\vec{e}_1, \vec{e}_2, \cdots, \vec{e}_N\} \rightarrow \{P\vec{e}_1, P\vec{e}_2, \cdots, P\vec{e}_N\}$$

Diagonalization:

By using eigenvectors as a basis,
we can obtain a simple linear map
represented by a diagonal matrix.

$$A \rightarrow P^{-1}AP$$

* The determinant of *A* is invariant under this transformation:

$$\det(P^{-1}AP) = \det(P^{-1})\det(A)\det(P^{-1}) = \det(A)\det(P^{-1}P) = \det(A)$$

$$\det(A) = \prod_i^N \lambda_i$$

(This relation is true even if *A* cannot be diagonalized)

Unitary matrix

Unitary matrix（ユニタリ行列）：$U^\dagger = U^{-1}$

Real Orthogonal matrix（実直交行列）：$P^t = P^{-1}, (P_{ij} \in \boldsymbol{R})$

When we consider a unitary matrix as a set of vectors:

$$U = (\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_N)$$

it is a orthonormal basis: $\vec{v}_i^* \cdot \vec{v}_j = \delta_{i,j}$

The linear map represented by a unitary matrix (**unitary transformation**) does not change

- the norm of a vector

$$||U\vec{v}|| = ||\vec{v}||$$

- "distance" between two vectors

$$||U\vec{v}_1 - U\vec{v}_2|| = ||\vec{v}_1 - \vec{v}_2||$$

Normal matrix

Normal matrix（正規行列）： $A^\dagger A = AA^\dagger$

We can always diagonalize it by a unitary matrix

$$U^\dagger = U^{-1}$$

as

$$U^\dagger A U = \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N \end{pmatrix} \qquad \lambda_i \in \boldsymbol{C}$$

Its eigenvalues could be complex.
(even if A is a real matrix)

Hermitian matrix and its eigenvalue

Hermitian matrix（エルミート行列）：$A^\dagger = A$

Real symmetric matrix（実対称行列）：$A^t = A, \quad (A_{ij} \in \boldsymbol{R})$

It is a special normal matrix. $A^\dagger A = AA^\dagger = AA$

Its eigenvalues are real.

We can always diagonalize it by a unitary matrix

$$U^\dagger A U = \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N \end{pmatrix} \qquad \lambda_i \in \boldsymbol{R}$$

Hermitian (or real symmetric) matrices often appear in physics.

Generalization of diagonalization

- Eigenvalue problems and diagonalizations are defined for a square matrix.
- Even if A is a square matrix, it may not be diagonalized.

  - Is it possible to transform all square matrixes into diagonal forms by generalizing the diagonalization?
  - Is it possible to generalize it to a rectangular matrices?

Yes. The **singular value decomposition** (特異値分解) is an generalization of the diagonalization.

Next week

第１回：　現代物理学における巨大なデータ
第２回：　情報圧縮と繰り込み
第３回：　情報圧縮の数理１　(線形代数の復習)

第４回：　情報圧縮の数理２　(特異値分解と低ランク近似)

(Singular value decomposition and low rank approximation)

第５回：　情報圧縮の数理３　(スパース・モデリングの基礎)
第６回：　情報圧縮の数理４　(クリロフ部分空間法の基礎)
第７回：　物質科学における情報圧縮
第８回：　スパース・モデリングの物質科学への応用
第９回：　クリロフ部分空間法の物質科学への応用
第１０回：　行列積表現の基礎
第１１回：　行列積表現の応用
第１２回：　テンソルネットワーク表現への発展
第１３回：　テンソルネットワーク繰り込みと低ランク近似の応用