

Singular Value Decomposition: Reduced Density Matrix

We will introduce the singular value decomposition of a matrix in the context of the reduced density matrix of a quantum system connected to an environment.

REDUCED DENSITY MATRIX¹

Let us consider a quantum system (block) B , which is spanned by the N -dimensional orthonormal basis set $\{|i\rangle \mid i = 1, \dots, N\}$, surrounded by an environment E , which is spanned by the M -dimensional orthonormal basis set $\{|j\rangle \mid j = 1, \dots, M\}$ (see the figure below).



The ground state of the total (= block + environment) system can be represented as

$$|\psi\rangle = \sum_{i=1}^N \sum_{j=1}^M \psi_{ij} |i\rangle |j\rangle. \quad (1)$$

Now consider the expectation value of an arbitrary operator, A , which acts only within the block:

$$\begin{aligned} \langle A \rangle &= \sum_i \sum_j \psi_{ij}^* \langle i | A \sum_{i'} \sum_{j'} \psi_{i'j'} |i'\rangle |j'\rangle \\ &= \sum_i \sum_j \sum_{i'} \sum_{j'} \psi_{i'j'} \psi_{ij}^* \langle i | A |i'\rangle \langle j | j'\rangle \\ &= \sum_i \sum_{i'} \sum_j \psi_{i'j} \psi_{ij}^* \langle i | A |i'\rangle \\ &\equiv \sum_i \sum_{i'} \rho_{i'i} A_{ii'} = \text{tr}_B(\rho A) \end{aligned} \quad (2)$$

where the reduced density matrix is defined as

$$\rho_{i'i} \equiv \sum_j \psi_{i'j} \psi_{ij}^* \quad (3)$$

and the matrix element of the operator is $A_{ii'} \equiv \langle i | A |i'\rangle$.

SINGULAR VALUE DECOMPOSITION (SVD)

Problem: What is the optimal reduced density matrix ρ of rank- m ($\ll N$)?

Solution: Singular value decomposition (SVD) of $\psi \in \mathbf{R}^N \times \mathbf{R}^M$.

(Theorem) An $N \times M$ matrix ψ (assume $N \geq M$) can be decomposed as (see [Appendix A](#) for proof of SVD and associated polar decomposition)

$$\begin{bmatrix} \psi \end{bmatrix} = \begin{bmatrix} U \end{bmatrix} \begin{bmatrix} d_1 \\ \vdots \\ d_M \end{bmatrix} \begin{bmatrix} V^T \end{bmatrix}, \quad (4)$$

or

$$\psi = U D V^T, \quad (5)$$

where $U = [U_{iv} = u_i^{(v)}] \in \mathbf{R}^N \times \mathbf{R}^M$ is column orthogonal, i.e.,

$$\sum_{i=1}^N u_i^{(v)} u_i^{(v')} = \delta_{vv'}, \quad (6)$$

or

¹ R. P. Feynman, *Statistical Mechanics* (Benjamin/Cummings, Reading, MA, 1972) Chap. 2.

$$U^T U = I_M, \quad (7)$$

and $V = [V_{iv} = v_i^{(v)}] \in \mathbf{R}^M \times \mathbf{R}^M$ is column orthogonal, *i.e.*,

$$\sum_{i=1}^M v_i^{(v)} v_i^{(v')} = \delta_{vv'}, \quad (8)$$

or

$$V^T V = I_M. \quad (9)$$

The columns of U , whose same-numbered elements d_v are *nonzero*, are an orthonormal set of basis vectors that span the range (see [Appendix B](#) for the range); the columns of V , whose same-numbered elements d_v are *zero*, are an orthonormal basis for the nullspace that is mapped to zero, *i.e.*, the subspace of $x \in \mathbf{R}^M$, where $\psi x = 0$. The program, `singular.c`, in the source code directory of the class home page demonstrates this automatic construction of orthonormal bases for the range and the nullspace.

TRUNCATED SVD AS OPTIMAL APPROXIMATION

(Theorem) Let $\psi = UDV^T$ be the SVD of ψ with the diagonal elements in descending order $d_1 \geq d_2 \geq \dots \geq d_M$ and let

$$\psi^{(m)} \equiv \sum_{v=1}^m u^{(v)} d_v v^{(v)T}, \quad (10)$$

be the rank- m truncation of the SVD. Then

$$\min_{\text{rank}(A)=m} \|A - \psi\|_2 = \|\psi^{(m)} - \psi\|_2 = d_{m+1}, \quad (11)$$

where the matrix 2-norm is defined in terms of the vector 2-norm as $\|A\|_2 = \min_{\|x \in \mathbf{R}^M\|_2=1} \|Ax\|_2$.

Therefore, $\psi^{(m)}$ is the optimal rank- m approximation to ψ .

Equation (10) shows that SVD is a representation of a matrix as a sum of outer products of two vectors, just as a density matrix is.

LOW-RANK APPROXIMATION TO THE REDUCED DENSITY MATRIX

Substituting the rank- m approximation (10) in the definition of the reduced density matrix, Eq. (3),

$$\begin{aligned} \rho &= \psi \psi^T \\ &= \sum_{v=1}^m \sum_{v'=1}^m u^{(v)} d_v (v^{(v)T} v^{(v')}) d_{v'} u^{(v')T} \\ &= \sum_{v=1}^m \sum_{v'=1}^m u^{(v)} d_v (d_{vv'}) d_{v'} u^{(v')T} \\ &= \sum_{v=1}^m u^{(v)} d_v^2 u^{(v)T} \end{aligned} \quad (12)$$

(Summary) The rank- m truncation of the SVD of the global (= block + environment) ground state wave function,

$$\psi^{(m)} = \sum_{v=1}^m u^{(v)} d_v v^{(v)T}, \quad (13)$$

or

$$\psi_{ij}^{(m)} = \sum_{v=1}^m u_{i(v)} d_v v_{j(v)}, \quad (14)$$

produces the rank- m approximation to the reduced density matrix,

$$\rho^{(m)} = \sum_{v=1}^m u^{(v)} w_v u^{(v)T}, \quad (15)$$

or

$$\rho_{ii'}^{(m)} = \sum_{\nu=1}^m u_{i(\nu)} w_{\nu} u_{i'(\nu)}, \quad (16)$$

where $w_{\nu} = d_{\nu}^2$. The rank- m approximation $\rho^{(m)}$ is optimal in the least square sense.

DENSITY MATRIX RENORMALIZATION GROUP

The density matrix renormalization group (DMRG) algorithm by Steven White² is a systematic procedure to accurately obtain a quantum ground state with a modest computational cost. The DMRG incrementally add environments to the block, solve the global (= block + environment) ground state, and construct a low-rank block density matrix to represent the block with reduced degrees of freedom.

Appendix A — Polar and Singular-Value Decompositions

A.1 POLAR DECOMPOSITION

(Theorem) Let \mathbf{A} be a real $N \times M$ matrix, where $N \geq M$ (i.e., mapping from an M -dimensional source vector space to a larger N -dimensional target vector space). Then, there exists a column-wise orthogonal matrix \mathbf{S} ($\in \mathfrak{R}^{N \times M}$ and) such that

$$\mathbf{A} = \mathbf{S}\mathbf{J}, \quad (\text{A1})$$

$$\mathbf{S}^T \mathbf{S} = \mathbf{I}^{M \times M}, \quad (\text{A2})$$

where $\mathbf{I}^{M \times M}$ is the identity matrix and the unique nonnegative matrix \mathbf{J} is

$$\mathbf{J} = \sqrt{\mathbf{A}^T \mathbf{A}} \in \mathfrak{R}^{M \times M}. \quad (\text{A3})$$

(Proof) Consider a spectral (or eigen) decomposition of \mathbf{J} :

$$\mathbf{J} = \sum_{i=1}^M \lambda_i |i\rangle\langle i|, \quad (\text{A4})$$

where λ_i (≥ 0) is the i -th eigenvalue and $\{|i\rangle \in \mathfrak{R}^M \mid i = 1, \dots, M\}$ is an orthonormal set of eigenvectors, where $\langle i|j\rangle = \delta_{i,j}$. Define a mapped N -element vector

$$|\psi_i\rangle = \mathbf{A}|i\rangle \in \mathfrak{R}^N, \quad (\text{A5})$$

then

$$\langle \psi_i | \psi_j \rangle = \langle i | \mathbf{A}^T \mathbf{A} | j \rangle = \langle i | \mathbf{J}^2 | j \rangle = \lambda_j^2 \langle i | j \rangle = \lambda_j^2 \delta_{i,j}. \quad (\text{A6})$$

For those eigenvectors with $\lambda_i \neq 0$, define

$$|e_i\rangle = |\psi_i\rangle / \lambda_i \in \mathfrak{R}^N, \quad (\text{A7})$$

so that these vectors are orthonormal, i.e., $\langle e_i | e_j \rangle = \delta_{i,j}$. For those eigenvectors with $\lambda_i = 0$, we use the Gram-Schmidt procedure to construct an orthonormal basis set and append it to the above basis set. Define a column-wise orthogonal matrix,

$$\mathbf{S} = \sum_{i=1}^M |e_i\rangle\langle i| \in \mathfrak{R}^{N \times M} \quad (\text{A8})$$

(note $\mathbf{S}^T \mathbf{S} = \sum_{i=1}^M |i\rangle\langle e_i| \sum_{j=1}^M |e_j\rangle\langle j| = \sum_{i=1}^M \sum_{j=1}^M |i\rangle \underbrace{\langle e_i | e_j \rangle}_{\delta_{ij}} \langle j| = \sum_{i=1}^M |i\rangle\langle i| = \mathbf{I}^{M \times M}$.) When $\lambda_i \neq 0$, we

have

$$\mathbf{S}\mathbf{J}|i\rangle = \sum_{j=1}^M |e_j\rangle \lambda_i \underbrace{\langle j | i \rangle}_{\delta_{ji}} = \lambda_i |e_i\rangle = |\psi_i\rangle = \mathbf{A}|i\rangle. \quad (\text{A9})$$

When $\lambda_i = 0$,

$$\mathbf{S}\mathbf{J}|i\rangle = \sum_{j=1}^M |e_j\rangle \underbrace{\lambda_i}_{0} \underbrace{\langle j | i \rangle}_{\delta_{ji}} = 0 |e_i\rangle = 0 = |\psi_i\rangle = \mathbf{A}|i\rangle. \quad (\text{A10})$$

Namely, $\mathbf{S}\mathbf{J}$ is identical to \mathbf{A} as a mapping for the entire M -dimensional source vector space. //

² S. R. White, "Density-matrix algorithms for quantum renormalization groups," *Physical Review B* **48**, 10345 (1993).

A.2 SINGULAR VALUE DECOMPOSITION

(Theorem) Let \mathbf{A} be a real $N \times M$ matrix, where $N \geq M$ as above. Then, there exists column-wise orthogonal matrices \mathbf{U} ($\in \mathfrak{R}^{N \times M}$) and \mathbf{V} ($\in \mathfrak{R}^{M \times M}$), such that

$$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^T, \quad (\text{A11})$$

$$\mathbf{U}^T\mathbf{U} = \mathbf{V}^T\mathbf{V} = \mathbf{I}^{M \times M}, \quad (\text{A12})$$

where \mathbf{D} ($\in \mathfrak{R}^{M \times M}$) is a nonnegative diagonal matrix.

(Proof) Consider the polar decomposition, $\mathbf{A} = \mathbf{S}\mathbf{J}$, in Eq. (A1). We perform the eigen-decomposition of \mathbf{J} as

$$\mathbf{J} = \mathbf{V}\mathbf{D}\mathbf{V}^T, \quad (\text{A13})$$

where \mathbf{D} is the diagonal matrix such that its matrix elements are

$$D_{ij} = \lambda_i \delta_{ij}, \quad (\text{A14})$$

and \mathbf{V} ($\in \mathfrak{R}^{M \times M}$) is an orthogonal matrix, *i.e.*, $\mathbf{V}^T\mathbf{V} = \mathbf{I}^{M \times M}$. Substituting Eq. (A13) in Eq. (A1), we have

$$\mathbf{A} = \mathbf{S}\mathbf{V}\mathbf{D}\mathbf{V}^T \equiv \mathbf{U}\mathbf{D}\mathbf{V}^T, \quad (\text{A15})$$

Note that $\mathbf{U} = \mathbf{S}\mathbf{V}$ ($\in \mathfrak{R}^{N \times M}$) is a column-wise orthogonal, since

$$\mathbf{U}^T\mathbf{U} = \mathbf{V}^T\mathbf{S}^T\mathbf{S}\mathbf{V} = \mathbf{V}^T \underbrace{\mathbf{S}^T\mathbf{S}}_{\mathbf{I}^{M \times M}} \mathbf{V} = \mathbf{V}^T\mathbf{V} = \mathbf{I}^{M \times M}. //$$

Appendix B — Rank and Range of a Matrix

For an $N \times M$ matrix A , consider the mapping,

$$x(\in R^M) \xrightarrow{A} b = Ax(\in R^N). \quad (\text{B1})$$

The *range* of matrix A is the vector space spanned by all linearly independent vectors $\{b\}$, which are mapped from some x . The *rank* of matrix A is the size (*i.e.*, the number of linearly independent vectors) of its range.