

4. Unitaries and isometries

TNB.4

Unitaries (unitary = invertible distance-preserving linear map)

A square matrix $\mathcal{U} \in \text{mat}(D, D; \mathbb{C})$ is called 'unitary' if it satisfies:

$$\mathcal{U}^\dagger \mathcal{U} = \mathbf{1}_D$$

$$(1a) \Leftrightarrow \mathcal{U}^\dagger = \mathcal{U}^{-1}$$

$$\mathcal{U} \mathcal{U}^\dagger = \mathbf{1}_D$$

$$(1b)$$

$$D \square D \square D = D$$

$$D \square D \square D = D$$

$$D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} \cdot D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} = D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array}$$

$$D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} \cdot D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} = D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array}$$

Its column vectors, $\mathcal{U} = (\vec{u}_1, \vec{u}_2, \dots, \vec{u}_D)$, form a basis for \mathbb{C}^D

Its D row vectors also form a basis for \mathbb{C}^D

$$\mathcal{U} \text{ defines an invertible map: } \begin{array}{c} \text{position } j \\ \begin{array}{|c|c|c|}\hline & 0 & \\ \hline & \vdots & \\ \hline & 1 & \\ \hline \end{array} \end{array} = \begin{array}{c} \text{column } j \\ | \\ \begin{array}{|c|c|c|}\hline 0 & & \\ \hline \vdots & & \\ \hline 1 & & \\ \hline \end{array} \end{array} = \vec{u}_j \in \mathbb{C}^D, \quad j = 1, \dots, D \quad (3a)$$

$$\mathcal{U}: \mathbb{C}^D \rightarrow \mathbb{C}^D, \quad \vec{e}_j \mapsto \mathcal{U} \vec{e}_j := \vec{e}_i \mathcal{U}^i{}_j = \vec{u}_j \quad (i, j \in 1, \dots, D) \quad (3b)$$

$$\text{standard basis vector in } \mathbb{C}^D : \quad \vec{e}_i = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \end{pmatrix}_{\text{position } i}$$

Its inverse is given by

$$\mathcal{U}^\dagger = \mathcal{U}^\dagger: \mathbb{C}^D \rightarrow \mathbb{C}^D, \quad \vec{e}_i \mapsto \mathcal{U}^\dagger(\vec{e}_i) = \vec{e}_k \mathcal{U}^{k i}$$

$$\text{Indeed, then } \mathcal{U}^\dagger \vec{u}_j \stackrel{(3b)}{=} \mathcal{U}^\dagger \vec{e}_i \mathcal{U}^i{}_j \stackrel{(4)}{=} \vec{e}_k \mathcal{U}^{k i} \mathcal{U}^i{}_j \stackrel{(1a)}{=} \vec{e}_j \quad \checkmark \quad (5)$$

consistent with (3b)

Left isometry (isometry = distance-preserving linear map, not necessarily invertible)

A rectangular matrix $A \in \text{mat}(D, D'; \mathbb{C})$ with $D \geq D'$ is called a 'left isometry' if (6a) holds:

$$D \square D' \square D$$

$$A^\dagger A = \mathbf{1}_{D'} \quad (6a)$$

Note: if $D > D'$ then

$$A A^\dagger \neq \mathbf{1}_D \quad (6b)$$

$$D \square D' \square D$$

$$D' \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} \cdot D \begin{array}{|c|c|c|}\hline D' & D' & D' \\ \hline \end{array} = D' \begin{array}{|c|c|c|}\hline D' & D' & D' \\ \hline \end{array}$$

$$D \begin{array}{|c|c|c|}\hline D' & D' & D' \\ \hline \end{array} \cdot D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array} = D \begin{array}{|c|c|c|}\hline D & D & D \\ \hline \end{array}$$

Its D' column vectors, $A = (\vec{a}_1, \vec{a}_2, \dots, \vec{a}_{D'})$, are orthonormal,

$$\vec{a}_i^\dagger \cdot \vec{a}_j \stackrel{(6a)}{=} \delta_{ij} \quad (7)$$

$$\vec{a}_i^\dagger = \vec{a}_i^\top$$

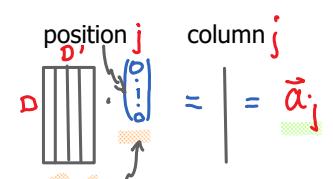
They form a basis for a D' -dimensional (sub)space of \mathbb{C}^D space of D -dimensional column vectors

$$u = u_1$$

They form a basis for a D' -dimensional (sub)space of $\mathbb{C}^{D'}$, space of D -dimensional column vectors

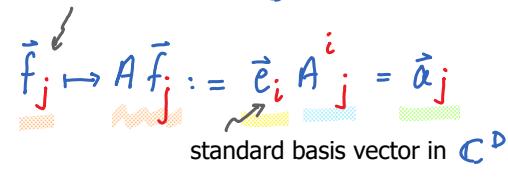
say $V_A = \text{span}\{\vec{a}_1, \vec{a}_2, \dots, \vec{a}_{D'}\}$ $\left\{ \begin{array}{ll} \subset \mathbb{C}^D & \text{true subspace if } D' \leq D \\ = \mathbb{C}^{D'} & \text{if } D' = D \end{array} \right.$ (9)

[The D row vectors of A each are elements of $\mathbb{C}^{D \times 1}$, not $\mathbb{C}^{1 \times D}$]
 ↪ dual space of D -dimensional row vectors

A defines an isometric map:  $= | = \vec{a}_j \in \mathbb{C}^D, j = 1, \dots, D'$ (9a)

Formally:

$$A : \mathbb{C}^{D'} \rightarrow \mathbb{C}^D, \quad \begin{matrix} \text{short} \\ \text{column} \\ \text{vectors} \end{matrix} \quad \begin{matrix} \text{long} \\ \text{column} \\ \text{vectors} \end{matrix}$$

 $f_j \mapsto A f_j := \vec{e}_i A^i_j = \vec{a}_j \quad j \in 1, \dots, D' \quad i \in 1, \dots, D$ (9b)

(9b): many (D) long columns are superposed to yield a smaller number (D') of orthonormal long columns.

These span $V_A \subsetneq \mathbb{C}^D$, the 'image space of A ' or 'image of A ', with dimension $\dim(A) = D'$.
 ↪ because A has fewer columns than rows

Invariance of scalar product (hence the name: iso-metric = equal metric):

If $A : \mathbb{C}^{D'} \rightarrow \mathbb{C}^D, \vec{x} \mapsto \vec{y} = A \vec{x}$, then

$$\|\vec{y}\|_{D'}^2 = \vec{y}^T \cdot \vec{y} = \vec{x}^T \underbrace{A^T A}_{I_{D'}} \vec{x} = \vec{x}^T \cdot \vec{x} = \|\vec{x}\|_{D'}^2 \quad (10)$$

Left projector

$$\underbrace{\mathbb{D} \mathbb{D}' \mathbb{D}}_{= P = AA^T} = \underbrace{AA^T}_{= I_{D'}} = \underbrace{\mathbb{D} \mathbb{D}'}_{= \mathbb{D}} = \underbrace{\mathbb{D}}_{= \mathbb{D}} \quad (11)$$

is a projector, since $P^2 = \underbrace{(AA^T)(AA^T)}_{(6a)} = AA^T = P$ $\quad (12)$

$$\underbrace{\mathbb{D} \mathbb{D}' \mathbb{D} \mathbb{D}}_{= P^2} = \underbrace{\mathbb{D} \mathbb{D}}_{= P}$$

Its action leaves V_A invariant, because it leaves each of its basis vectors invariant: $\quad (13)$

$$P \vec{a}_j = \underbrace{AA^T}_{(6a)} A \vec{f}_j = A \vec{f}_j = \vec{a}_j \quad (9b)$$

Right isometry

A rectangular matrix $\mathcal{B} \in \text{mat}(D, D'; \mathbb{C})$ with $D \leq D'$ is called a 'right isometry' if (14a) holds:

$$\begin{array}{c} D \\ \odot \\ D' \end{array}$$

$$\mathcal{B} \mathcal{B}^\dagger = \mathbf{1}_D \quad (14a)$$

Note: if $D < D'$ then

$$\mathcal{B}^\dagger \mathcal{B} \neq \mathbf{1}_{D'} \quad (14b)$$

$$\begin{array}{c} D \\ \odot \\ D' \end{array} \quad \begin{array}{c} D \\ \odot \\ D' \end{array} = \begin{array}{c} D \\ \odot \\ D \end{array}$$

$$\begin{array}{c} D' \\ \odot \\ D \end{array} \cdot \begin{array}{c} D \\ \odot \\ D' \end{array} = \begin{array}{c} D' \\ \odot \\ D' \end{array}$$

Its D row vectors, $\mathcal{B} = \begin{pmatrix} \vec{b}^1 \\ \vec{b}^2 \\ \vdots \\ \vec{b}^D \end{pmatrix}$, are orthonormal, $\vec{b}^i \cdot \vec{b}^{i\dagger} = \delta^{ii}$. (15)

[row vectors (dual to column vectors)
are labeled using upstairs index]

space of D' -dimensional row vectors

They form a basis for a D -dimensional (sub)space of $\mathbb{C}^{D'*}$,

$$\text{say } \mathcal{V}_\mathcal{B}^* = \text{span}\{\vec{b}^1, \vec{b}^2, \dots, \vec{b}^D\} \quad \left\{ \begin{array}{ll} \subset \mathbb{C}^{D'*} & \text{true subspace if } D < D' \\ = \mathbb{C}^{D'*} & \text{if } D = D' \end{array} \right. \quad (16)$$

[The D' column vectors of \mathcal{B} each are elements of \mathbb{C}^D , not $\mathbb{C}^{D'}$.]

\mathcal{B} defines an isometric map: $(0 \dots 1_{..0}) \cdot \begin{array}{c} \text{position } i \\ \odot \\ D' \end{array} = \text{row } i = \vec{b}^i \in \mathbb{C}^{D'*}, i = 1, \dots, D$ (17a)

standard basis vector in $\mathbb{C}^{D'*}$

$$\mathcal{B}: \mathbb{C}^{D*} \rightarrow \mathbb{C}^{D'*}, \quad \begin{array}{c} \text{short} \\ \text{row} \\ \text{vectors} \end{array} \quad \begin{array}{c} \text{long} \\ \text{row} \\ \text{vectors} \end{array} \quad \vec{f}^i \mapsto \vec{f}^i \mathcal{B} := \mathcal{B}^i_j \vec{e}^j = \vec{b}^i \quad i \in 1, \dots, D \quad j \in 1, \dots, D' \quad (17b)$$

standard basis vector in \mathbb{C}^{D*}

(17b) says: many (D') long rows are superposed to yield a smaller number (D) of orthonormal long rows.

These span $\mathcal{V}_\mathcal{B}^* \subseteq \mathbb{C}^{D'*}$, the 'image space of \mathcal{B} ' or 'image of \mathcal{B} ', with dimension $\dim(\mathcal{B}) = D$.
 \subsetneq if \mathcal{B} has fewer rows than columns

Invariance of scalar product

(hence the name: iso-metric = equal metric):

If $\mathcal{B}: \mathbb{C}^{D*} \rightarrow \mathbb{C}^{D'*}$, $\bar{x} \mapsto \bar{y} = \bar{x} \mathcal{B}$, then

$$\|\bar{y}\|_{D'*}^2 = \bar{y} \cdot \bar{y}^\dagger = \bar{x} \underbrace{\mathcal{B} \mathcal{B}^\dagger}_{\mathbf{1}_{D'}} \bar{x}^\dagger = \bar{x} \cdot \bar{x}^\dagger = \|\bar{x}\|_{D*}^2 \quad (18)$$

Right projector

$$\overset{D'}{\overrightarrow{D}} \otimes \overset{D'}{\overrightarrow{D}} = P = B^+ B = \overset{D}{\overrightarrow{D}} \cdot \overset{D'}{\overrightarrow{D}} = \overset{D'}{\overrightarrow{D}} \quad (19)$$

is a projector, since $P^2 = (B^+ B)(B^+ B) = B^+ B = P$ (20)

(14a) $\overbrace{B^+ B} = \mathbf{1}_D$

Its action leaves V_B^* invariant, since it leaves its basis vectors invariant:

$$\overset{D}{\overleftarrow{B}} P = \overset{D}{\overleftarrow{B}} B^+ B = \overset{D}{\overleftarrow{B}} = \overset{D}{\overleftarrow{B}} \quad (21)$$

(14a) $\overbrace{B^+ B} = \mathbf{1}$

Truncation of unitaries yield isometries

Consider a unitary, $D \times D$ matrix, $U^\dagger U = \mathbf{1}_D$, (22)

and partition its columns into two groups, containing D' and $\bar{D}' = D - D'$ columns:

$$U = (\bar{u}_1, \bar{u}_2, \dots, \bar{u}_{D'}, \bar{u}_{D'+1}, \dots, \bar{u}_D) = (\bar{u}_1, \dots, \bar{u}_{D'}) \oplus (\bar{u}_{D'+1}, \dots, \bar{u}_D) =: A \oplus \bar{A} \quad (23)$$

$$\overset{D}{\overrightarrow{U}} = \overset{D'}{\overrightarrow{U}} \oplus \overset{\bar{D}'}{\overrightarrow{U}} \quad (24)$$

Unitarity of U implies:

$$\begin{pmatrix} \mathbf{1}_{D'} \\ \mathbf{1}_{\bar{D}'} \end{pmatrix} = \mathbf{1}_D = U^\dagger U = \begin{pmatrix} A^\dagger \\ \bar{A}^\dagger \end{pmatrix} (A, \bar{A}) = \begin{pmatrix} A^\dagger A & A^\dagger \bar{A} \\ \bar{A}^\dagger A & \bar{A}^\dagger \bar{A} \end{pmatrix} \quad (25)$$

$$\begin{array}{c} \boxed{\begin{array}{|c|c|} \hline \diagup & \circ \\ \hline \circ & \diagdown \\ \hline \end{array}} \\ = \end{array} \begin{array}{c} \boxed{\begin{array}{|c|} \hline \diagup \\ \hline \end{array}} \\ = \end{array} \begin{array}{c} \overset{D'}{\overrightarrow{U}} \\ \oplus \\ \overset{\bar{D}'}{\overrightarrow{U}} \end{array} \cdot \begin{array}{c} \overset{D'}{\overrightarrow{U}} \\ \oplus \\ \overset{\bar{D}'}{\overrightarrow{U}} \end{array} \quad (26)$$

Hence, A and \bar{A} are both isometries:

$$\begin{array}{l} \boxed{\overset{D}{\overrightarrow{D}} \otimes \overset{D'}{\overrightarrow{D}}} \quad \boxed{\overset{D}{\overrightarrow{D}} \otimes \overset{\bar{D}'}{\overrightarrow{D}}} \\ = A^\dagger A \stackrel{(25)}{=} \mathbf{1}_{D'}, \quad \overset{\bar{D}'}{\overrightarrow{D}} \otimes \overset{D}{\overrightarrow{D}} = \bar{A}^\dagger \bar{A} \stackrel{(25)}{=} \mathbf{1}_{\bar{D}'} \end{array} \quad (27)$$

$$\begin{array}{c} \text{Diagram showing } \bar{D}' \cdot D = \bar{D}' \bar{D}^T, \\ \text{Diagram showing } \bar{D}' \cdot \bar{D} = \bar{D}' \bar{D}^T \end{array} \quad (28)$$

Moreover, A and \bar{A} are orthogonal to each other, since they are built from orthogonal column vectors:

$$\begin{array}{c} \text{Diagram showing } \bar{D}' \cdot D = A^T A, \\ \text{Diagram showing } \bar{D}' \cdot \bar{D} = \bar{A}^T \bar{A} \end{array} \quad (29)$$

$$\begin{array}{c} \text{Diagram showing } \bar{D}' \cdot D = \bar{D}' \bar{D}^T, \\ \text{Diagram showing } \bar{D}' \cdot \bar{D} = \bar{D}' \bar{D}^T \end{array} \quad (30)$$

Complementary projectors

The projectors, $P = AA^T = \bar{D} \bar{D}^T \bar{D}^T D$, $\bar{P} = \bar{A}\bar{A}^T = \bar{D} \bar{D}^T \bar{D}^T \bar{D}$ (31)

$$= \bar{D} \cdot \bar{D}^T \bar{D}^T D, \quad = \bar{D} \bar{D}^T \cdot \bar{D}^T \bar{D}$$

are both $D \times D$ matrices,

and satisfy orthonormality relations:

$$P \cdot P \stackrel{(27)}{=} P, \quad \bar{P} \cdot \bar{P} \stackrel{(27)}{=} \bar{P}, \quad P \cdot \bar{P} \stackrel{(29)}{=} 0, \quad \bar{P} \cdot P \stackrel{(29)}{=} 0 \quad (32)$$

E.g.: $P \cdot \bar{P} = \underbrace{A A^T \bar{A} \bar{A}^T}_{(29) = 0} = \underbrace{-D \bar{D}^T \bar{D}^T D}_{(29) = 0} = 0$ (34)

They split \mathbb{C}^D into two orthogonal and hence complementary subspaces:

$$P : \mathbb{C}^D \rightarrow \mathbb{V}_A = \text{span}\{\bar{u}_1, \dots, \bar{u}_{D'}\} =: \text{span}\{\bar{a}_1, \dots, \bar{a}_{D'}\} \subsetneq \mathbb{C}^D \quad (35)$$

$$\bar{P} : \mathbb{C}^D \rightarrow \mathbb{V}_{\bar{A}} = \text{span}\{\bar{u}_{D'+1}, \dots, \bar{u}_D\} =: \text{span}\{\bar{a}_{D'+1}, \dots, \bar{a}_D\} \subsetneq \mathbb{C}^D \quad (36)$$

with $\bar{x}^\dagger \bar{y} = 0 \quad \forall \bar{x} \in \mathbb{V}_A, \bar{y} \in \mathbb{V}_{\bar{A}}$ (37)

In this sense, isometries (more precisely, their projectors) map large vector spaces into smaller ones.

Conversely: any left (or right) isometry can be extended to a unitary by adding orthonormal columns (or rows) orthogonal to those already present.

$$\begin{array}{ccc} \text{Diagram showing } \bar{D}' \rightarrow \bar{D}' \bar{D}^T \bar{D}^T D, \\ \text{Diagram showing } \bar{D}' \rightarrow \bar{D}' \bar{D}^T \bar{D}^T \bar{D} \end{array} \quad (38)$$

$$\begin{array}{ccc} \text{Diagram showing } D \rightarrow D \bar{D}^T \bar{D}^T \bar{D}, \\ \text{Diagram showing } D \rightarrow D \bar{D}^T \bar{D}^T \bar{D} \end{array} \quad (39)$$

A discussion similar to the above holds for splitting a unitary matrix into two sets of rows, yielding two right isometries.

5. Singular value decomposition (SVD)

[Schollwoeck2011, Sec. 4]

TNB.5

https://en.wikipedia.org/wiki/Singular_value_decomposition

Consider a $D \times D'$ matrix, $M \in \text{mat}(D, D'; \mathbb{C})$ and let $\tilde{D} = \min(D, D')$ (1)

Theorem: Any such M has a singular value decomposition (SVD) of the form

$$M = U \cdot S \cdot V^T$$

$D \times D' \quad D \times \tilde{D} \quad \tilde{D} \times \tilde{D} \quad \tilde{D} \times D'$

$$M = \begin{array}{c} U \\ \otimes \\ S \\ \otimes \\ V^T \end{array} \quad (2)$$

or 

where

$U \in \text{mat}(D, \tilde{D}; \mathbb{C})$ satisfies

$$U^T U = \mathbf{1}_{\tilde{D}}$$

$$\begin{array}{c} U^T \\ \otimes \\ U \end{array} = \mathbf{1}_{\tilde{D}} \quad (3)$$

$V^T \in \text{mat}(\tilde{D}, D'; \mathbb{C})$ satisfies

$$V^T V = \mathbf{1}_{\tilde{D}}$$

$$\begin{array}{c} V^T \\ \otimes \\ V \end{array} = \mathbf{1}_{\tilde{D}} \quad (4)$$

(5)

$S \in \text{mat}(\tilde{D}, \tilde{D}; \mathbb{R})$ is diagonal, with real, non-negative diagonal elements, called 'singular values'

=

Remarks:

(i) SVD ingredients can be found by diagonalization of the hermitian matrices MM^T and $M^T M$.

$$D \times D: \quad MM^T \stackrel{(2)}{=} (USV^T)(V^T U^T) \stackrel{(4)}{=} US^2 U^T \stackrel{(3)}{\Rightarrow} D \times \tilde{D}: \quad MM^T U = US^2 \quad (6)$$

$$D' \times D': \quad M^T M \stackrel{(2)}{=} (V^T U^T)(U S V^T) \stackrel{(3)}{=} VS^2 V^T \stackrel{(4)}{\Rightarrow} D' \times \tilde{D}: \quad M^T M V = VS^2 \quad (7)$$

So, eigenvectors of MM^T yield columns of U , eigenvectors of $M^T M$ yield columns of V .

They have the same set of eigenvalues, yielding the squares of the singular values.

(ii) Properties of S

- diagonal matrix, of dimension $\tilde{D} \times \tilde{D}$, with $\tilde{D} = \min(D, D')$ (8)

- diagonal elements can be chosen non-negative, are called 'singular values' $S_\alpha := S_{\alpha\alpha} = \tilde{d}$ 

- 'Schmidt rank' r : number of non-zero singular values

- arrange in descending order: $s_1 \geq s_2 \geq \dots \geq s_r > 0$ (9)

$$\Rightarrow S = \text{diag}(s_1, s_2, \dots, s_r, \underbrace{0, \dots, 0}_{\tilde{D}-r} \text{ zeros}) \quad (10)$$

(iii) Properties of U and V^T :

$$\tilde{D} = \min(D, D')$$

- $\dim(U) = D \times \tilde{D}$, $U^T U = \mathbf{1}_{\tilde{D}}$, columns of U are orthonormal. (11)

- $\dim(U) = D \times \tilde{D}$, $U^T U = \mathbb{1}_{\tilde{D}}$, columns of U are orthonormal. (11)
- If $D = \tilde{D}$, then U is unitary. If $D > \tilde{D}$, then U is a left isometry. (12)
- $\dim(V^T) = \tilde{D} \times D'$, $V^T V = \mathbb{1}_{\tilde{D}}$, rows of V^T are orthonormal. (13)
- If $\tilde{D} = D'$, then V^T is unitary. If $\tilde{D} < D'$, then V^T is a right isometry. (14)

(iv) Visualization

If $\tilde{D} = D \leq D'$:

$$M = D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} = D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} = U \cdot S \cdot V^T \quad (15)$$

U is unitary:

$$U^T U = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \mathbb{1}_{\tilde{D}} \quad (16)$$

product is arranged such that the outer indices have the smallest dimension, \tilde{D}

V^T is right isometry:

$$V^T V = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \mathbb{1}_{\tilde{D}} \quad (17)$$

If $D \geq D' = \tilde{D}$:

$$M = D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} = D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} = U \cdot S \cdot V^T \quad (18)$$

U is left isometry:

$$U^T U = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \mathbb{1}_{\tilde{D}} \quad (19)$$

product is arranged such that the outer indices have the smallest dimension, \tilde{D}

V^T is unitary:

$$V^T V = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{D'} \cdot \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \tilde{D} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}^{\tilde{D}} = \mathbb{1}_{\tilde{D}} \quad (20)$$

(vi) Truncation via SVD

Def: Frobenius norm: $\|M\|_F^2 := \sum_{\alpha\beta} |M_{\alpha\beta}|^2 = \sum_{\alpha\beta} \overline{M_{\alpha\beta}} M_{\alpha\beta} = \sum_{\alpha\beta} M_{\beta\alpha}^T M_{\alpha\beta} = \text{Tr } M^T M \quad (21)$

$\dots + \dots + \dots + \dots - \sqrt{\dots} \quad \boxed{\dots}$

$$\text{evaluated via SVD: } \quad = \text{Tr}(\underbrace{V S U^T}_{=1} U S V^T) = \text{Tr}(\underbrace{V^T}_{=1} \underbrace{V S^2}_{\text{trace is cyclic}}) = \boxed{\text{Tr } S^2} \quad (22)$$

singular values determine norm

Truncation

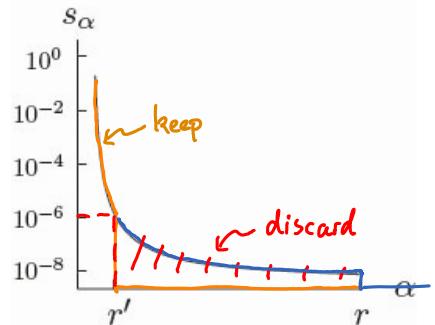
SVD can be used to approximate a rank r matrix M by a rank $r' (< r)$ matrix M' :

Suppose $M = U S V^T$ (23)

with $S = \text{diag}(s_1, s_2, \dots, s_r, \underbrace{0, \dots, 0}_{\tilde{D} - r \text{ zeros}})$ (24)

Truncate: $M' := U S' V^T$ (25)

with $S' := \text{diag}(s_1, s_2, \dots, s_{r'}, \underbrace{0, \dots, 0}_{\tilde{D}' - r' \text{ zeros}})$ (26)



Retain only r' largest singular values!

Visualization, with $\tau = \tilde{D}$:

$$\tilde{D} = D \leq D': \quad D \boxed{M} = D \begin{array}{c|c|c} \tilde{D} & \tilde{D} & D' \\ \hline \vdots & \diagdown & \vdots \\ \vdots & \vdots & \vdots \end{array} \quad (27)$$

$$D \boxed{M'} = D \begin{array}{c|c|c} D' & r' & D' \\ \hline \vdots & \begin{matrix} r' \\ 0 \end{matrix} & \vdots \\ \vdots & \diagdown & \vdots \\ \vdots & 0 & \vdots \end{array} = D \begin{array}{c|c|c} r' & r' & D' \\ \hline \vdots & \diagdown & \vdots \\ \vdots & \vdots & \vdots \end{array} \quad (28)$$

$$D \geq D' = \tilde{D}: \quad D \boxed{M} = D \begin{array}{c|c|c} \tilde{D} & \tilde{D} & D' \\ \hline \vdots & \diagdown & \vdots \\ \vdots & \vdots & \vdots \end{array} \quad (29)$$

$$D \boxed{M'} = D \begin{array}{c|c|c} D' & r' & D' \\ \hline \vdots & \begin{matrix} r' \\ 0 \end{matrix} & \vdots \\ \vdots & \diagdown & \vdots \\ \vdots & 0 & \vdots \end{array} = D \begin{array}{c|c|c} r' & r' & D' \\ \hline \vdots & \diagdown & \vdots \\ \vdots & \vdots & \vdots \end{array} \quad (30)$$

SVD truncation yields 'optimal' approximation of a rank r matrix M by a rank $r' (< r)$ matrix M' , in the sense that it can be shown to minimize the Frobenius norm of the difference, $\|M - M'\|_F$.

$$\|M - M'\|_F^2 = \text{Tr}((M - M')^T(M - M')) = \text{Tr}(M^T M + M'^T M' - M'^T M - M^T M') \quad (31)$$

similar steps as for (8)

$$\begin{aligned} &= \text{Tr}(\cancel{S \cdot S} + \cancel{S' \cdot S'} - \cancel{S' \cdot S} - \cancel{S \cdot S'}) \\ &\quad \xrightarrow{\cancel{S' \cdot S} = S' \cdot S' = S' \cdot S'} \\ &\quad \boxed{\begin{matrix} \diagdown & \diagdown \\ 0 & \diagdown \end{matrix}} = \boxed{\begin{matrix} \diagdown & \diagdown \\ 0 & \diagdown \end{matrix}} \end{aligned} \quad (32)$$

'discarded weight'

$$\begin{array}{c}
 \boxed{0} \quad \boxed{\diagdown} = \boxed{0} \quad \boxed{0} \\
 = \text{Tr} \left(S^2 - S'^2 \right) = \sum_{\alpha=1}^r s_\alpha^2 - \sum_{\alpha=1}^{r'} s_\alpha^2 = \boxed{\sum_{\alpha=r'+1}^r s_\alpha^2} \quad (33)
 \end{array}$$

Note:

$$u u^T M v v^T = u u^T U S V^T v v^T = u S v^T = M'$$

$$\boxed{\parallel} \cdot \boxed{\text{skew}} \cdot \boxed{\parallel} = \boxed{\parallel} \cdot \boxed{\parallel} \cdot \boxed{\parallel} \cdot \boxed{\diagdown} \cdot \boxed{\parallel} \cdot \boxed{\parallel} = \boxed{\parallel} \cdot \boxed{0} \cdot \boxed{\parallel}$$

(vi) Polar decomposition of square matrix

Any square matrix can be factored into a Hermitian, positive matrix and a unitary matrix:

$$M = u S v^+ = \begin{cases} (u S u^+) (u v^+) \\ (u v^+) (v S v^+) \end{cases} = \begin{cases} P W \\ \tilde{W} \tilde{P} \end{cases} \quad \begin{matrix} \text{'left polar decomposition'} \\ \text{'right polar decomposition'} \end{matrix} \quad (34)$$

This generalizes the polar decomposition for complex numbers, $z = |z| e^{i\phi}$

QR-decomposition

If singular values are not needed,

a $D \times D'$ matrix M

has the 'full QR decomposition'

$$M = Q R \quad (35)$$

with Q a $D \times D$ unitary matrix,

$$D \leq D': \quad D \boxed{D'} = D \boxed{\parallel} \boxed{0} \boxed{\text{mymy}}$$

$$M = Q \quad R$$

$$D \geq D': \quad D \boxed{D'} = D \boxed{\parallel} \boxed{0} \boxed{\text{m}}$$

$$Q Q^+ = Q^+ Q = \mathbb{1} \quad (36)$$

and R a $D \times D'$ upper triangular matrix,

$$R_{\alpha\beta} = 0 \quad \text{if } \alpha > \beta \quad (37)$$

If $D \geq D'$, then M has the 'thin QR decomposition'

$$M = (Q_1, Q_2) \cdot \begin{pmatrix} R_1 \\ 0 \end{pmatrix} = Q_1 \cdot R_1 \quad (38)$$

with $\dim(Q_1) = D \times D'$, $\dim(R_1) = D' \times D'$, $Q_1^+ Q_1 = \mathbb{1}$ but $Q_1 Q_1^+ \neq \mathbb{1}$ and R_1 upper triangular.

$$\boxed{Q_1 \quad Q_2} \boxed{R_1 \quad 0} = \boxed{Q_1} \boxed{R_1}$$

QR-decomposition is numerically cheaper than SVD, but has less information (not 'rank-revealing').

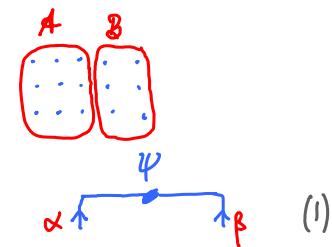
6. Schmidt decomposition [most efficient way of representing entanglement]

TNB.6

[most efficient way of representing entanglement]

Consider a quantum system composed of two subsystems, A and B ,

with orthonormal bases $\{|\alpha\rangle_A\}$ and $\{|\beta\rangle_B\}$.



$$\text{Pure state on } A \cup B: |\psi\rangle = |\alpha\rangle_A |\beta\rangle_B \psi^{\alpha\beta}$$

Reduced density matrices of subsystem A :

$$Tr_B |\beta\rangle\langle\beta| = S_B^B$$

$$\hat{\rho}_A = Tr_B |\psi\rangle\langle\psi| = Tr_B \psi^{\alpha\beta} |\alpha\rangle_A |\beta\rangle_B \langle\beta| \langle\alpha| \overline{\psi^{\alpha\beta}} = |\alpha\rangle_A \psi^{\alpha\beta} \psi_{\beta\alpha}^+ \langle\alpha| \quad (2)$$

$$= |\alpha\rangle_A (\rho_A)^{\alpha}_{\alpha'} \langle\alpha'|, \quad \text{with} \quad (\rho_A)^{\alpha}_{\alpha'} = (\psi\psi^+)^{\alpha}_{\alpha'} \quad (3)$$

Singular value decomposition

Use SVD to find bases for A and B

$$|\psi\rangle \stackrel{\text{SVD}}{=} U S V^+$$

which diagonalize density matrices:

With indices:

$$|\psi\rangle = U_A^\alpha S^{\lambda\lambda'} V_B^{\beta} \quad \xrightarrow{\text{diag}(S_1, S_2, \dots)} \quad |\psi\rangle = U_A^\alpha \lambda \lambda' V_B^{\beta} \quad (5)$$

$$\text{Hence } |\psi\rangle = |\lambda\rangle_A |\lambda\rangle_B \quad S^{\lambda\lambda'} = \sum_{\lambda} |\lambda\rangle_A |\lambda\rangle_B S_{\lambda} \quad (6)$$

$$\text{where } |\lambda\rangle_A = |\alpha\rangle_A U_A^\alpha \lambda, \quad U_A^\alpha \xrightarrow{\alpha} \lambda; \quad |\lambda\rangle_B = |\beta\rangle_B V_B^{\beta} \lambda', \quad V_B^{\beta} \xrightarrow{\beta} \lambda' \quad (7)$$

are orthonormal sets of states for A and B , and can be extended to yield orthonormal bases for A and B if needed.

Orthonormality is guaranteed by

$$U^\dagger U = \mathbb{1} \quad \text{and} \quad V^\dagger V = \mathbb{1} ! \quad (8)$$

$$\langle \lambda' | \lambda \rangle_A = U_A^\alpha \lambda' \langle \alpha | U_A^\alpha \lambda = U_A^\alpha \lambda' U_A^\alpha \lambda = \mathbb{1}^{\lambda'} \lambda = \begin{bmatrix} 1 \\ \lambda' \end{bmatrix} \quad (9)$$

$$\langle \lambda' | \lambda \rangle_B = V_B^{\beta} \lambda' \langle \beta | V_B^{\beta} \lambda = V_B^{\beta} \lambda' V_B^{\beta} \lambda = \mathbb{1}_{\lambda'} \lambda = \begin{bmatrix} 1 \\ \lambda' \end{bmatrix} \quad (10)$$

Restrict \sum_{λ} to the r non-zero singular values:

$$|\psi\rangle = \sum_{\lambda=1}^r |\lambda\rangle_A |\lambda\rangle_B s_{\lambda} \quad \text{'Schmidt decomposition'} \quad (11)$$

If $r=1$, 'classical' state: $|\psi\rangle = |\downarrow\rangle_B |\downarrow\rangle_A$. If $r \geq 1$: 'entangled state'

In this representation, reduced density matrices are diagonal:

$$\hat{\rho}_A = T_{\tau_B} |\psi\rangle\langle\psi| = \sum_{\lambda} |\lambda\rangle_A (s_{\lambda})^2 \langle\lambda| \quad (12)$$

$$(\psi\psi^T), (\psi^T\psi) \text{ with } \psi^{xx'} = s_{\lambda} \mathbb{1}^{xx'} \quad (13)$$

$$\hat{\rho}_B = T_{\tau_A} |\psi\rangle\langle\psi| = \sum_{\lambda} |\lambda\rangle_B (s_{\lambda})^2 \langle\lambda| \quad (14)$$

$$\text{Entanglement entropy: } S_{A/B} = - \sum_{\lambda=1}^r (s_{\lambda})^2 \ln_2 (s_{\lambda})^2 \quad (15)$$

Note: for given r , entanglement is maximal if all singular values are equal, $s_{\lambda} = r^{-1/2}$

$$\text{Then, } S_{A/B} = \ln r \quad (\text{this proves TNB1.13}) \quad (16)$$

How can one approximate $|\psi\rangle = \sum_{\alpha\beta} |\alpha\rangle_A |\beta\rangle_B \psi^{\alpha\beta}$ by cheaper $|\tilde{\psi}\rangle$?

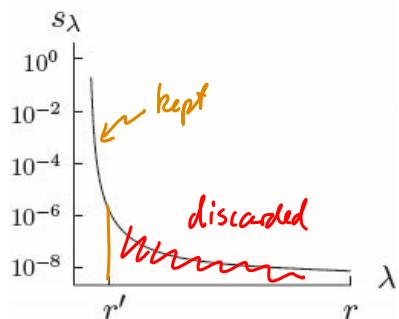
$$\| |\psi\rangle \|_2^2 \equiv |\langle\psi|\psi\rangle|^2 = \sum_{\alpha\beta} |\psi^{\alpha\beta}|^2 = \| \psi \|_F^2 \quad (17)$$

Define truncated state using r' ($< r$) singular values:

$$|\tilde{\psi}\rangle = \sum_{\lambda=1}^{r'} |\lambda\rangle_A |\lambda\rangle_B s_{\lambda} \quad (18)$$

Truncation error:

$$\begin{aligned} \| |\psi\rangle - |\tilde{\psi}\rangle \|_2^2 &= \langle\psi|\psi\rangle + \langle\tilde{\psi}|\tilde{\psi}\rangle - 2 \operatorname{Re} \langle\tilde{\psi}|\psi\rangle \\ &= \sum_{\lambda=1}^r (s_{\lambda})^2 + \sum_{\lambda=1}^{r'} (s_{\lambda})^2 - \sum_{\lambda=1}^{r'} (s_{\lambda})^2 = \sum_{\lambda=r'+1}^r (s_{\lambda})^2 \quad (19) \\ &= \text{sum of squares of discarded singular values} \end{aligned}$$



Useful to obtain 'cheap' representation of $|\psi\rangle$ if singular values decay rapidly.

If $|\tilde{\psi}\rangle$ should be normalized, rescale, i.e. replace s_{λ} by $s_{\lambda} \left[\sum_{\lambda=1}^{r'} (s_{\lambda})^2 \right]^{-1/2}$ (20)

The truncation strategy (18) minimizes the truncation error.

It is used over and over again in tensor network numerics.