

#### 4. Unitaries and isometries

TNB.4

Unitaries (unitary = invertible distance-preserving linear map)

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

$$D \text{ --- } \square \text{ --- } D$$

$$U^{\dagger} U = \mathbb{1}_D \quad (1a) \Leftrightarrow U^{\dagger} = U^{-1} \Leftrightarrow U U^{\dagger} = \mathbb{1}_D \quad (1b)$$

$$D \text{ --- } \square \text{ --- } D \text{ --- } \square \text{ --- } D = D$$

$$D \text{ --- } \square \text{ --- } D \text{ --- } \square \text{ --- } D = D$$

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

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

Its column vectors,  $U = (\vec{u}_1, \vec{u}_2, \dots, \vec{u}_D)$ , form a basis for  $\mathbb{C}^D$  (2)

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

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

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

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

Its inverse is given by

$$U^{-1} = U^{\dagger}: \mathbb{C}^D \rightarrow \mathbb{C}^D, \quad \vec{e}_i \mapsto U^{\dagger}(\vec{e}_i) = \vec{e}_k U^{\dagger k}_i \quad (4)$$

$$\text{Indeed, then } U^{\dagger} \vec{u}_j \stackrel{(3b)}{=} U^{\dagger} \vec{e}_i U^i_j \stackrel{(4)}{=} \vec{e}_k U^{\dagger k}_i U^i_j \stackrel{(1a)}{=} \delta_{kj} = \vec{e}_j \quad \text{consistent with (3b)} \quad (5)$$

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:

$$D \text{ --- } D \text{ --- } D'$$

$$A^{\dagger} A = \mathbb{1}_{D'} \quad (6a) \quad \text{Note: if } D > D' \text{ then } A A^{\dagger} \neq \mathbb{1} \quad (6b)$$

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

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

Its  $D'$  column vectors,  $A = (\vec{a}_1, \vec{a}_2, \dots, \vec{a}_{D'})$ , are orthonormal,  $\vec{a}_i^{\dagger} \cdot \vec{a}_j \stackrel{(6a)}{=} \delta_{ij} \quad (7)$

$$\vec{a}_i^{\dagger} = \overline{\vec{a}_i}^T$$

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

$$u - u_i$$

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

say  $V_A = \text{span}\{\bar{a}_1, \bar{a}_2, \dots, \bar{a}_{D'}\} \begin{cases} \subsetneq \mathbb{C}^D & \text{true subspace if } D' < D \\ = \mathbb{C}^D & \text{if } D' = D \end{cases} \quad (9)$

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

$A$  defines an isometric map:  $\begin{matrix} \text{position } j \\ \text{column } j \end{matrix} \begin{matrix} D' \\ D \end{matrix} \begin{matrix} \text{column } j \\ \text{position } j \end{matrix} = \bar{a}_j \in \mathbb{C}^D, \quad j = 1, \dots, D' \quad (9a)$

Formally:

$A: \mathbb{C}^{D'} \rightarrow \mathbb{C}^D$ ,   
 short column vectors  $\rightarrow$  long column vectors   
 $\bar{f}_j \mapsto A \bar{f}_j = \bar{e}_i A_{ij} = \bar{a}_j$    
 standard basis vector in  $\mathbb{C}^{D'}$    
 standard basis vector in  $\mathbb{C}^D$    
 $j \in 1, \dots, D'$    
 $i \in 1, \dots, D$    
 (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  $A: \mathbb{C}^{D'} \rightarrow \mathbb{C}^D$ ,  $\bar{x} \mapsto \bar{y} = A \bar{x}$ , then

$$\|\bar{y}\|_D^2 = \bar{y}^\dagger \cdot \bar{y} = \bar{x}^\dagger \underbrace{A^\dagger A}_{\mathbb{I}_{D'}} \bar{x} = \bar{x}^\dagger \bar{x} = \|\bar{x}\|_{D'}^2, \quad (10)$$

Left projector

$$\begin{matrix} D & D' & D & D \end{matrix} = P = A A^\dagger = \begin{matrix} D' \\ D \end{matrix} \cdot \begin{matrix} D \end{matrix} = \begin{matrix} D \end{matrix} \quad (11)$$

is a projector, since  $P^2 = \underbrace{(A A^\dagger)}_{\mathbb{I}_{D'}} (A A^\dagger) = A A^\dagger = P$    
 $\begin{matrix} D & D' & D & D \end{matrix} = \begin{matrix} D & D' & D \end{matrix}$    
 (12)

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

$$P \bar{a}_j \stackrel{(11, 9b)}{=} \underbrace{A A^\dagger A}_{(6a) = \mathbb{I}_{D'}} \bar{f}_j = A \bar{f}_j \stackrel{(9b)}{=} \bar{a}_j$$

## Right isometry

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

$$B B^\dagger = \mathbb{1}_D \quad (14a) \quad \text{Note: if } D < D' \text{ then } B^\dagger B \neq \mathbb{1}_{D'} \quad (14b)$$

Its  $D$  row vectors,  $B = \begin{pmatrix} \vec{b}^1 \\ \vec{b}^2 \\ \vdots \\ \vec{b}^D \end{pmatrix}$ , are orthonormal,  $\vec{b}^i \cdot \vec{b}^j = \delta^{ij}$ . (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  $\mathbb{C}^{D'*}$

say  $V_B^* = \text{span}\{\vec{b}^1, \vec{b}^2, \dots, \vec{b}^D\}$   $\begin{cases} \subsetneq \mathbb{C}^{D'*} & \text{true subspace if } D < D' \\ = \mathbb{C}^{D'*} & \text{if } D = D' \end{cases}$  (16)

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

$B$  defines an isometric map:  $(0 \dots 1 \dots 0)^{D'} = \text{row } i = \vec{b}^i \in \mathbb{C}^{D'*}, i = 1, \dots, D$  (17a)

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

$B: \mathbb{C}^{D'*} \rightarrow \mathbb{C}^{D'*}$ ,  $\vec{f}^i \mapsto \vec{f}^i B := B^i_j \vec{e}^j = \vec{b}^i$   $i \in 1, \dots, D$  (17b)

short row vectors      long row vectors

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

## Invariance of scalar product

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

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

$$\|\vec{y}\|_{D'}^2 = \vec{y} \cdot \vec{y}^\dagger = \vec{x} B B^\dagger \vec{x}^\dagger = \vec{x} \cdot \vec{x}^\dagger = \|\vec{x}\|_{D'}^2 \quad (18)$$

## Right projector

$$\overbrace{D' \rightarrow D \rightarrow D'}^{D'} = P = B^\dagger B = \begin{matrix} D \\ \downarrow \\ D' \end{matrix} \cdot \begin{matrix} D' \\ \leftarrow \\ D \end{matrix} = \begin{matrix} D' \\ \downarrow \\ \text{shaded box} \end{matrix} \quad (19)$$

is a projector, since  $P^2 = \underbrace{(B^\dagger B)}_{(14a)} \underbrace{(B^\dagger B)}_{\mathbb{1}_D} = B^\dagger B = P$  (20)

$$\overbrace{D \rightarrow D \rightarrow D \rightarrow D}^{D'} = \overbrace{D \rightarrow D}^{D'}$$

Its action leaves  $\bigvee_B^*$  invariant, since it leaves its basis vectors invariant:

$$\vec{b}^i P \stackrel{(19, 17b)}{=} \vec{f}^i_B \underbrace{B^\dagger B}_{(14a) = \mathbb{1}} = \vec{f}^i_B \stackrel{(17b)}{=} \vec{b}^i \quad \checkmark \quad (21)$$

## Truncation of unitaries yield isometries

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

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

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

$$\begin{matrix} D \\ \downarrow \\ U \end{matrix} = \begin{matrix} D' \\ \downarrow \\ A \end{matrix} \oplus \begin{matrix} \bar{D}' \\ \downarrow \\ \bar{A} \end{matrix} \quad (24)$$

Unitarity of  $U$  implies:

$$\begin{pmatrix} \mathbb{1}_{D'} & 0 \\ 0 & \mathbb{1}_{\bar{D}'} \end{pmatrix} = \mathbb{1}_D = U^\dagger U = \begin{pmatrix} A^\dagger \\ \bar{A}^\dagger \end{pmatrix} (A, \bar{A}) = \begin{pmatrix} A^\dagger A & A^\dagger \bar{A} \\ \bar{A}^\dagger A & \bar{A}^\dagger \bar{A} \end{pmatrix} \quad (25)$$

$$\begin{matrix} \begin{smallmatrix} \square & \square \\ \square & \square \end{smallmatrix} \\ = \\ \square \\ = \\ \begin{smallmatrix} \text{rows} \\ \text{columns} \end{smallmatrix} \end{matrix} \quad (26)$$

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

$$\overbrace{D \rightarrow D}^{D'} \quad \overbrace{D \rightarrow D}^{D'}$$

$$\overbrace{D \rightarrow D \rightarrow D}^{D'} = A^\dagger A \stackrel{(25)}{=} \mathbb{1}_{D'} \quad , \quad \overbrace{D \rightarrow D \rightarrow D}^{\bar{D}'} = \bar{A}^\dagger \bar{A} \stackrel{(25)}{=} \mathbb{1}_{\bar{D}'} \quad (27)$$

$$\begin{matrix} D' \\ \downarrow \\ \text{rows} \end{matrix} \cdot \begin{matrix} D' \\ \leftarrow \\ \text{columns} \end{matrix} = D' \begin{matrix} D' \\ \square \end{matrix} \quad , \quad \begin{matrix} D \\ \downarrow \\ \text{rows} \end{matrix} \cdot \begin{matrix} \bar{D}' \\ \leftarrow \\ \text{columns} \end{matrix} = \begin{matrix} \bar{D}' \\ \downarrow \\ \text{rows} \end{matrix} \cdot \begin{matrix} \bar{D}' \\ \leftarrow \\ \text{columns} \end{matrix}$$

$$\begin{aligned} \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} &= D' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad , \quad \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} = \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (28) \end{aligned}$$

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

$$\begin{aligned} \bar{A}^\dagger A &\stackrel{(25)}{=} 0 \quad , \quad A^\dagger \bar{A} \stackrel{(25)}{=} 0 \quad (29) \end{aligned}$$

$$\begin{aligned} \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} &= \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad , \quad D' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} = D' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (30) \end{aligned}$$

### Complementary projectors

The projectors,  $P = A A^\dagger = \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad , \quad \bar{P} = \bar{A} \bar{A}^\dagger = \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (31)$

$$\begin{aligned} &= D' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \cdot \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad , \quad = D \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \cdot \bar{D}' \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (32) \end{aligned}$$

are both  $D \times D$  matrices,  
and satisfy orthonormality relations:

$$P \cdot P \stackrel{(27)}{=} P \quad , \quad \bar{P} \cdot \bar{P} \stackrel{(27)}{=} \bar{P} \quad , \quad P \cdot \bar{P} \stackrel{(29)}{=} 0 \quad , \quad \bar{P} \cdot P \stackrel{(29)}{=} 0 \quad (33)$$

E.g.:  $P \cdot \bar{P} = A \underbrace{A^\dagger \bar{A}}_{\stackrel{(29)}{=} 0} \bar{A}^\dagger = \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} = 0 \quad (34)$

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

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

$$\bar{P} : \mathbb{C}^D \rightarrow V_{\bar{A}} = \text{span}\{\vec{u}_{D'+1}, \dots, \vec{u}_D\} =: \text{span}\{\vec{a}_1, \dots, \vec{a}_{D'}\} \subsetneq \mathbb{C}^D \quad (36)$$

with  $\vec{x}^\dagger \vec{y} = 0 \quad \forall \quad \vec{x} \in V_A, \quad \vec{y} \in V_{\bar{A}} \quad (37)$

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.

$$\begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \rightarrow \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (38)$$

$$\begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \rightarrow \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} \quad (39)$$

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

$$U = \begin{bmatrix} \text{yellow} \\ \text{green} \\ \text{blue} \\ \text{red} \end{bmatrix} = \begin{pmatrix} B \\ \bar{B} \end{pmatrix}$$

$$\begin{aligned} B B^\dagger &= 1 & B \bar{B}^\dagger &= 0 \\ \bar{B} \bar{B}^\dagger &= 1 & \bar{B} B^\dagger &= 0 \end{aligned}$$

## 5. Singular value decomposition (SVD)

[Schollwoeck2011, Sec. 4]

TNB.5

[https://en.wikipedia.org/wiki/Singular\\_value\\_decomposition](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

$$M = U \cdot S \cdot V^\dagger \quad (2)$$

where

$$U \in \text{mat}(D, \tilde{D}; \mathbb{C}) \text{ satisfies } U^\dagger U = \mathbb{1}_{\tilde{D}} \quad (3)$$

$$V^\dagger \in \text{mat}(\tilde{D}, D'; \mathbb{C}) \text{ satisfies } V^\dagger V = \mathbb{1}_{\tilde{D}} \quad (4)$$

$$S \in \text{mat}(\tilde{D}, \tilde{D}; \mathbb{R}) \text{ is diagonal, with real, non-negative diagonal elements, called 'singular values'} \quad (5)$$

Remarks:

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

$$MM^\dagger \stackrel{(2)}{=} (U S V^\dagger)(V S U^\dagger) \stackrel{(4)}{=} U S^2 U^\dagger \stackrel{(3)}{\Rightarrow} MM^\dagger U = U S^2 \quad (6)$$

$$M^\dagger M \stackrel{(2)}{=} (V S U^\dagger)(U S V^\dagger) \stackrel{(3)}{=} V S^2 V^\dagger \stackrel{(4)}{\Rightarrow} M^\dagger M V = V S^2 \quad (7)$$

So, eigenvectors of  $MM^\dagger$  yield columns of  $U$ , eigenvectors of  $M^\dagger M$  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'  $s_\alpha = S_{\alpha\alpha} = \tilde{\sigma}$

- '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  $V^\dagger$ :  $\tilde{D} = \min(D, D')$

- $\dim(U) = D \times \tilde{D}$ ,  $U^\dagger U = \mathbb{1}_{\tilde{D}}$ , 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  $V^T$  of 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  $\tilde{D} = D \leq D'$ :

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

$U$  is unitary:

$$U^T U = \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} \cdot \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} = \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} = \mathbb{1} \quad (16)$$

product is arranged such that the outer indices have the smallest dimension,

$V^T$  is right isometry:

$$V^T V = \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} \cdot \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} = \begin{array}{|c|} \hline \text{[Matrix]} \\ \hline \end{array} = \mathbb{1} \quad (17)$$

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

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

$U$  is left isometry:

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

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

$V^T$  is unitary:

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

#### (vi) Truncation via SVD

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



evaluated via SVD:

$$= \text{Tr} \left( \underbrace{V S^T U^T U S^T U^T}_{\text{trace is cyclic}} \right) = \text{Tr} \left( \underbrace{V^T V}_{=I} S^2 \right) = \text{Tr} S^2 \quad (22)$$

singular values determine norm

## Truncation

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

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

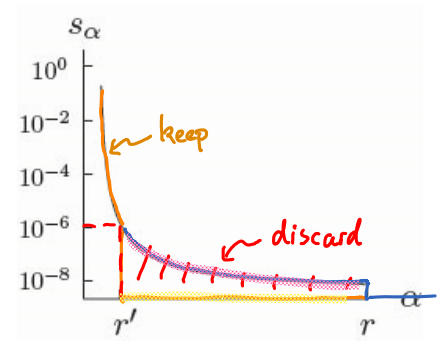
with  $S = \text{diag}(s_1, s_2, \dots, s_r, 0, \dots, 0)$  (24)

$\tilde{D} - r$  zeros

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

with  $S' := \text{diag}(s_1, s_2, \dots, s_{r'}, 0, \dots, 0)$  (26)

$\tilde{D} - r'$  zeros



Retain only  $\tau'$  largest singular values! Visualization, with  $\tau = \tilde{D}$ :

$$\tilde{D} = D \leq D': \quad D \begin{matrix} D' \\ M \end{matrix} = D \begin{matrix} \tilde{D} \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} \tilde{D} \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} \quad (27)$$

$$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} \quad (28)$$

$U \quad S' \quad V^T$

$$D \geq D' = \tilde{D} \quad D \begin{matrix} D' \\ M \end{matrix} = D \begin{matrix} \tilde{D} \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} \tilde{D} \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} \quad (29)$$

$$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} \text{vertical lines} \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} \text{diagonal} \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{horizontal lines} \end{matrix} \end{matrix} \quad (30)$$

$U \quad S' \quad V^T$

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

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

similar steps as for (8)

$$= \text{Tr} \left( \underbrace{S \cdot S}_{=S' \cdot S'} + \underbrace{S' \cdot S'}_{=S' \cdot S'} - \underbrace{S' \cdot S}_{=S' \cdot S'} - \underbrace{S \cdot S'}_{=S' \cdot S'} \right) \quad (32)$$

$$\begin{matrix} \text{diagonal} \\ 0 \end{matrix} \begin{matrix} \text{diagonal} \end{matrix} = \begin{matrix} \text{diagonal} \\ 0 \end{matrix} \begin{matrix} \text{diagonal} \\ 0 \end{matrix}$$

'discarded weight'

$$\begin{bmatrix} \diagup & \\ & 0 \end{bmatrix} \begin{bmatrix} \diagup & \\ & \diagup \end{bmatrix} = \begin{bmatrix} \diagup & \\ & 0 \end{bmatrix} \begin{bmatrix} \diagup & \\ & 0 \end{bmatrix}$$

'discarded weight'

$$= \text{Tr} (S^2 - S'^2) = \sum_{\alpha=1}^r s_{\alpha}^2 - \sum_{\alpha=1}^{r'} s_{\alpha}^2 = \sum_{\alpha=r'+1}^r s_{\alpha}^2 \quad (33)$$

Note:

$$u u^T M v v^T = u u^T U S V^T v v^T = u s v^T = u u^T$$

### (vi) Polar decomposition of square matrix

no negative eigenvalues

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

$$M = U S V^T = \begin{cases} (U S U^T)(U V^T) = P W & \text{'left polar decomposition'} \\ (U V^T)(V S V^T) = \tilde{W} \tilde{P} & \text{'right polar decomposition'} \end{cases} \quad (34)$$

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,

$$Q Q^T = Q^T Q = 1 \quad (36)$$

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

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

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

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

$$\begin{bmatrix} Q_1 & Q_2 \\ \hline & 0 \end{bmatrix} \begin{bmatrix} R_1 \\ \hline 0 \end{bmatrix} = \begin{bmatrix} Q_1 \\ \hline \end{bmatrix} \begin{bmatrix} R_1 \\ \hline \end{bmatrix}$$

with  $\dim(Q_1) = D \times D'$ ,  $\dim(R_1) = D' \times D'$ ,  
and  $R_1$  upper triangular.

$$Q_1^T Q_1 = 1 \text{ but } Q_1 Q_1^T \neq 1 \quad (39)$$

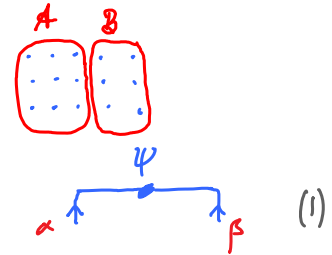
QR-decomposition is numerically cheaper than SVD, but has less information (not 'rank-revealing').



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

TNB.6

Consider a quantum system composed of two subsystems,  $A$  and  $B$ ,  
with orthonormal bases  $\{|\alpha\rangle_A\}$  and  $\{|\beta\rangle_B\}$ .



Pure state on  $A \cup B$ :  $|\psi\rangle = |\alpha\rangle_A |\beta\rangle_B \psi^{\alpha\beta}$  (1)

Reduced density matrices of subsystems  $A$  and  $B$ :  $\text{Tr}_B |\psi\rangle\langle\psi| = \delta_{\beta\beta'}$

$$\hat{\rho}_A = \text{Tr}_B |\psi\rangle\langle\psi| = \text{Tr}_B \psi^{\alpha\beta} |\alpha\rangle_A |\beta\rangle_B \langle\beta'|_B \langle\alpha'|_A \overline{\psi^{\alpha'\beta'}} = |\alpha\rangle_A \psi^{\alpha\beta} \overline{\psi^{\alpha'\beta'}} \langle\alpha'|_A \quad (2)$$

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

### Singular value decomposition

Use SVD to find bases for  $A$  and  $B$   
which diagonalize density matrices:

$$\psi \stackrel{\text{SVD}}{=} U S V^\dagger \quad (4)$$

With indices:

$$\psi^{\alpha\beta} = U^{\alpha}_{\lambda} S^{\lambda\lambda'} V^{\dagger}_{\lambda'}{}^{\beta} \quad (5)$$

$\uparrow$   
 $\text{diag}(s_1, s_2, \dots)$

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

where  $|\lambda\rangle_A = |\alpha\rangle_A U^{\alpha}_{\lambda}$ ,  $|\lambda\rangle_B = |\beta\rangle_B V^{\dagger}_{\lambda'}{}^{\beta}$  (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  $U^\dagger U = \mathbb{1}$  and  $V^\dagger V = \mathbb{1}$  ! (8)

$$\langle\lambda'|\lambda\rangle_A = U^{\dagger}_{\lambda'} U^{\alpha}_{\lambda} = \mathbb{1}^{\lambda'}_{\lambda} = \begin{cases} 1 & \lambda = \lambda' \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

$$\langle\lambda'|\lambda\rangle_B = V^{\dagger}_{\lambda'} V^{\beta}_{\lambda} = \mathbb{1}^{\lambda'}_{\lambda} = \begin{cases} 1 & \lambda = \lambda' \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

Restrict  $\sum_{\lambda}$  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:  $|\psi\rangle = |1\rangle_A |1\rangle_B$  If  $r > 1$ : 'entangled state'

In this representation, reduced density matrices are diagonal:

$$\hat{\rho}_A = \text{Tr}_B |\psi\rangle\langle\psi| = \sum_{\lambda} |\lambda\rangle_A (S_{\lambda})^2 \langle\lambda|_A \quad (12)$$

$$(\psi\psi^\dagger), (\psi^\dagger\psi) \text{ with } \psi^{\lambda\lambda'} = S_{\lambda} \mathbb{1}^{\lambda\lambda'} \quad (13)$$

$$\hat{\rho}_B = \text{Tr}_A |\psi\rangle\langle\psi| = \sum_{\lambda} |\lambda\rangle_B (S_{\lambda})^2 \langle\lambda|_B \quad (14)$$

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,  $S_{\lambda} = r^{-1/2}$

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

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

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

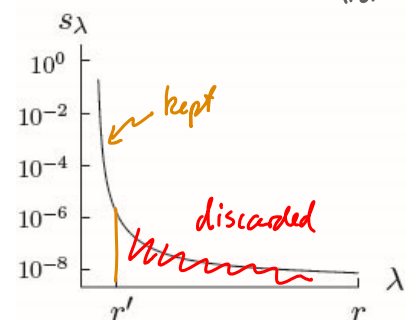
Define truncated state using  $r' (< r)$  singular values:

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

Truncation error:

$$\begin{aligned} \| |\psi\rangle - |\tilde{\psi}\rangle \|_2^2 &= \langle \psi | \psi \rangle + \langle \tilde{\psi} | \tilde{\psi} \rangle - 2 \text{Re} \langle \tilde{\psi} | \psi \rangle \\ &= \sum_{\lambda=1}^r (S_{\lambda})^2 + \sum_{\lambda=1}^{r'} (S_{\lambda})^2 - 2 \sum_{\lambda=1}^{r'} (S_{\lambda})^2 = \sum_{\lambda=r'+1}^r (S_{\lambda})^2 \quad (19) \end{aligned}$$

= sum of squares of discarded singular values = 'discarded weight'



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

If  $|\tilde{\psi}\rangle$  should be normalized, rescale, i.e. replace  $S_{\lambda}$  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.