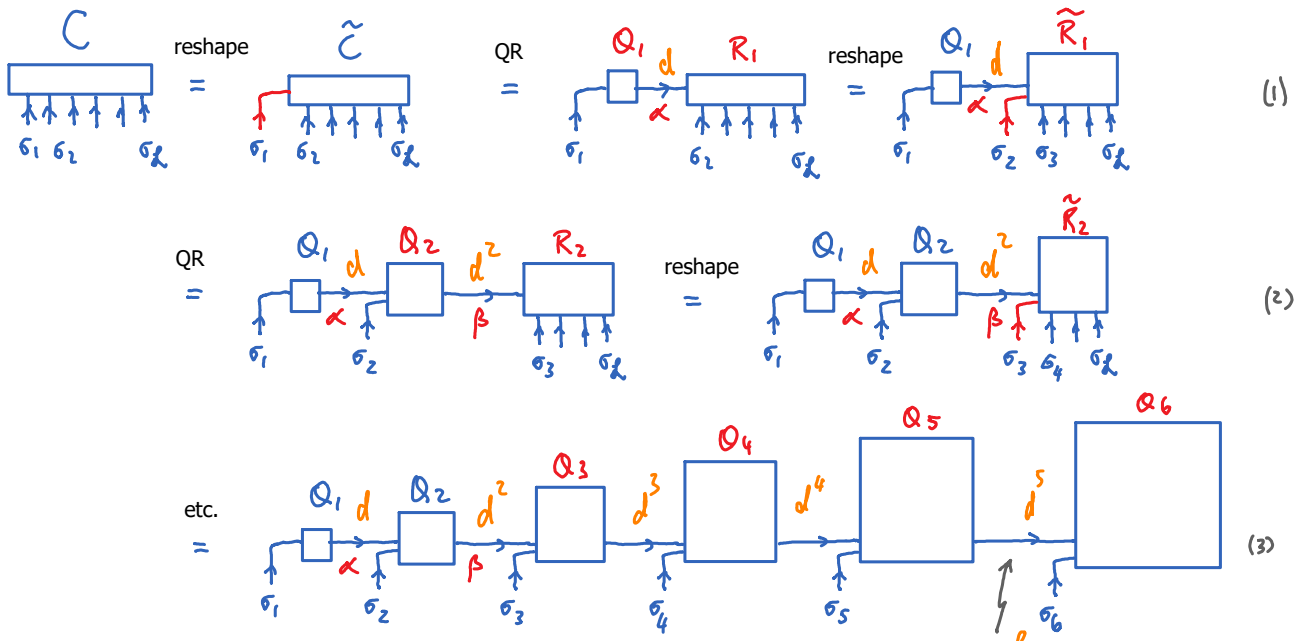


1. Reshaping generic tensor into MPS form

A generic tensor of arbitrary rank can be expressed as an MPS through repeated matrix factorizations, using QR decomposition, $M = QR$, or singular value decomposition (SVD): $M = U S V^T$



In formulas ('reshape' means regroup indices):

bond dimensions grow as d^l

$$C^{\sigma_1 \dots \sigma_L} \xrightarrow{\text{reshape}} \tilde{C}^{\sigma_1, \sigma_2 \dots \sigma_L} \xrightarrow{\text{QR}} Q_1^{\sigma_1} R_1^{\alpha, \sigma_2 \dots \sigma_L} \xrightarrow{\text{reshape}} Q_1^{\sigma_1} \tilde{R}_1^{\alpha \sigma_2, \sigma_3 \dots \sigma_L} \quad (4)$$

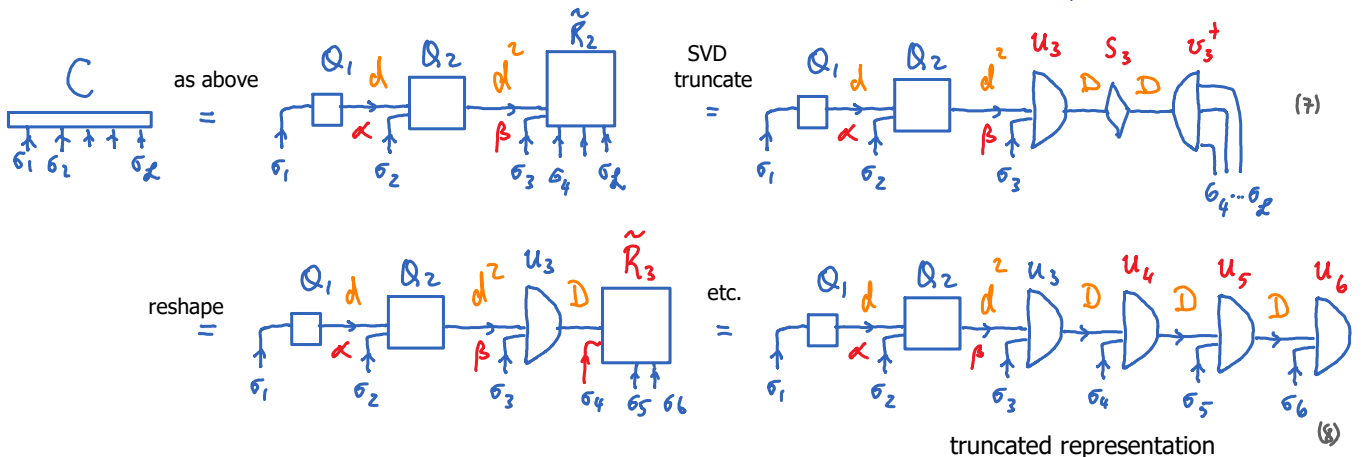
$$\xrightarrow{\text{QR}} Q_1^{\sigma_1} Q_2^{\alpha \sigma_2} R_2^{\beta, \sigma_3 \dots \sigma_L} \xrightarrow{\text{reshape}} Q_1^{\sigma_1} Q_2^{\alpha \sigma_2} \tilde{R}_2^{\beta \sigma_3, \sigma_4 \dots \sigma_L} = \dots \quad (5)$$

$$= Q_1^{\sigma_1} Q_2^{\alpha \sigma_2} Q_3^{\beta \sigma_3} \dots R_{L-1}^{\mu \sigma_L} \quad (6)$$

If a maximal bond dimension of $D \ll D$ is desired, this can be achieved using SVD instead of QR decompositions, and truncating by retaining only largest D singular values at each step:

$$R \stackrel{\text{SVD}}{=} U S V^T \quad (U \text{ and } V \text{ are isometries, } S \text{ is diagonal, with non-negative elements})$$

truncate $\approx U S V^T$ where S contains only largest D singular values of S



2. Unitaries and isometries (reminder)

TNB-III.2

Unitaries

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

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

$$D \times D \times D = D$$

$$D \times D \times D = D$$

$$D \begin{matrix} D \\ \hline \hline \hline \end{matrix} \cdot D \begin{matrix} D \\ \hline \hline \hline \end{matrix} = D \begin{matrix} D \\ \hline \hline \hline \end{matrix}$$

$$D \begin{matrix} D \\ \hline \hline \hline \end{matrix} \cdot D \begin{matrix} D \\ \hline \hline \hline \end{matrix} = D \begin{matrix} D \\ \hline \hline \hline \end{matrix}$$

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: $\begin{matrix} \text{position } j \\ \text{column } j \\ \hline \hline \hline \end{matrix} = \vec{u}_j \in \mathbb{C}^D, j=1, \dots, D$ (3a)

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

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

Its inverse is given by

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

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

Left isometry (isometry = distance-preserving map)

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

$$A^t A = \mathbb{1}_{D'} \quad (6a) \quad \text{Note: if } D > D' \text{ then } A A^t \neq \mathbb{1}_D \quad (6b)$$

$$D' \begin{matrix} D \\ \hline \hline \hline \end{matrix} \cdot D' \begin{matrix} D \\ \hline \hline \hline \end{matrix} = D' \begin{matrix} D \\ \hline \hline \hline \end{matrix}$$

$$D \begin{matrix} D' \\ \hline \hline \hline \end{matrix} \cdot D' \begin{matrix} D \\ \hline \hline \hline \end{matrix} = D \begin{matrix} D \\ \hline \hline \hline \end{matrix}$$

Its D' column vectors, $A = (\vec{a}_1, \vec{a}_2, \dots, \vec{a}_{D'})$, are orthonormal, $\vec{a}_i^t \cdot \vec{a}_j = \delta_{ij}$ (6a) (7)

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

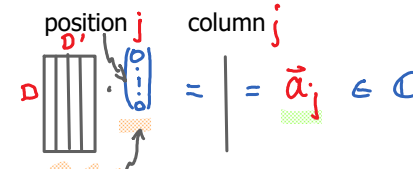
They form a basis for a D' -dimensional (sub)space of \mathbb{C}^D space of D -dimensional column vectors

$u - u_i$

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

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

[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:  $= \vec{a}_j \in \mathbb{C}^D, \quad j = 1, \dots, D' \quad (9a)$

Formally:

$A: \mathbb{C}^{D'} \rightarrow \mathbb{C}^D, \quad \vec{f}_j \mapsto A\vec{f}_j := \vec{e}_i A_{ij} = \vec{a}_j \quad \begin{matrix} j \in 1, \dots, D' \\ i \in 1, \dots, D \end{matrix} \quad (9b)$

short column vectors long column vectors

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

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

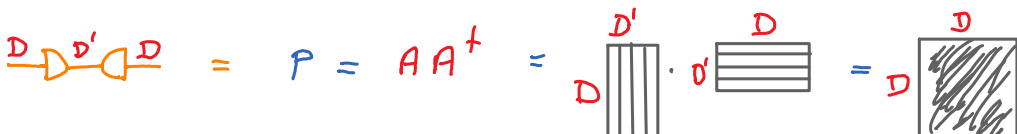
These span $V_A \subsetneq \mathbb{C}^D$, the 'image space of A ' or 'image of A ', with dimension $\dim(A) = D'$
 because A has fewer columns than rows

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


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

$$\|\vec{y}\|_D^2 = \vec{y}^t \cdot \vec{y} = \vec{x}^t \underbrace{A^t A}_{\mathbb{I}_{D'}} \vec{x} = \vec{x}^t \cdot \vec{x} = \|\vec{x}\|_{D'}^2 \quad (10)$$

Left projector

 $= P = AA^t = \begin{matrix} D \\ D' \end{matrix} \cdot \begin{matrix} D \\ D \end{matrix} = \begin{matrix} D \\ D \end{matrix} \quad (11)$

is a projector, since $P^2 = \underbrace{(AA^t)}_{(6a)} \underbrace{(AA^t)}_{\mathbb{I}_{D'}} = AA^t = P \quad (12)$



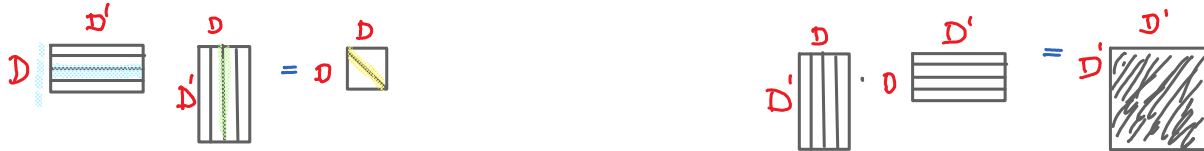
Its action leaves V_A invariant, because it leaves each its basis vectors invariant: (13)

$$P\vec{a}_j \stackrel{(11, 9b)}{=} \underbrace{AA^t A}_{(6a) = \mathbb{I}} \vec{f}_j = A\vec{f}_j \stackrel{(9b)}{=} \vec{a}_j$$

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:

$$B B^T = \mathbb{1}_D \quad (14a) \quad \text{Note: if } D < D' \text{ then } B^T B \neq \mathbb{1}_{D'} \quad (14b)$$



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: $\begin{pmatrix} 0 & \dots & 1 & \dots & 0 \end{pmatrix} \cdot \begin{matrix} \text{position } i \\ \text{row } i \\ \text{standard basis vector in } \mathbb{C}^{D'} \end{matrix} = \vec{b}^i \in \mathbb{C}^{D'}, i = 1, \dots, D$ (17a)

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

short row vectors long row vectors

standard basis vector in $\mathbb{C}^{D'}$ 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 $\dim(V_B^*) = D$. \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

$$\|\vec{y}\|_{\mathbb{C}^D}^2 = \vec{y} \cdot \vec{y}^t = \vec{x} B B^t \vec{x}^t = \vec{x} \cdot \vec{x}^t = \|\vec{x}\|_{\mathbb{C}^{D'}}^2 \quad (18)$$

$$\|\tilde{y}\|_{D'}^2 = \tilde{y} \cdot \tilde{y}^\dagger = \tilde{x} \underbrace{B B^\dagger}_{\mathbb{1}_{D'}} \tilde{x}^\dagger = \tilde{x} \cdot \tilde{x}^\dagger = \|\tilde{x}\|_{D'}^2 \quad (18)$$

Right projector

$$\underbrace{D \quad D}_{D'} \underbrace{D \quad D}_{D'} = P = B^\dagger B = \begin{array}{|c|} \hline D \\ \hline \end{array} \cdot \begin{array}{|c|} \hline D' \\ \hline \end{array} = \begin{array}{|c|} \hline D' \\ \hline \end{array} \quad (19)$$

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

$$\underbrace{D \quad D}_{D'} \underbrace{D \quad D}_{D'} = \underbrace{D \quad D}_{D'}$$

Its action leaves \mathbb{V}_B^* invariant, since it leaves its basis vectors invariant:

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

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:

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

$$D \begin{array}{|c|} \hline D \\ \hline \end{array} = \begin{array}{|c|} \hline D' \\ \hline \end{array} \oplus \begin{array}{|c|} \hline \bar{D}' \\ \hline \end{array} \quad (24)$$

$A \quad \bar{A}$

Unitarity of U implies:

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

$$\begin{array}{|c|c|} \hline \square & \square \\ \hline \square & \square \\ \hline \end{array} = \begin{array}{|c|} \hline D' \\ \hline \end{array} \begin{array}{|c|} \hline D' \\ \hline \end{array} \begin{array}{|c|} \hline \bar{D}' \\ \hline \end{array} \begin{array}{|c|} \hline \bar{D}' \\ \hline \end{array} \quad (26)$$

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

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

$$\begin{aligned}
 \begin{matrix} D \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} D' \\ \hline \hline \hline \end{matrix} &= \begin{matrix} D' \\ \hline \hline \hline \end{matrix} \\
 \begin{matrix} \hline \hline \hline \\ D \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ D' \end{matrix} &= \begin{matrix} \hline \hline \hline \\ D' \end{matrix}
 \end{aligned} \quad (28)$$

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

$$\begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} = \bar{A}^T A \stackrel{(25)}{=} 0, \quad \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} = A^T \bar{A} \stackrel{(25)}{=} 0 \quad (29)$$

$$\begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} = \begin{matrix} D' \\ \hline \hline \hline \\ 0 \end{matrix}, \quad \begin{matrix} \hline \hline \hline \\ D \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ D' \end{matrix} = \begin{matrix} \hline \hline \hline \\ 0 \end{matrix} \quad (30)$$

Complementary projectors

The projectors, $P = AA^T = \begin{matrix} D \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix}$, $\bar{P} = \bar{A}\bar{A}^T = \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \cdot \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix}$ (31)

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.: $P \cdot \bar{P} = A A^T \bar{A} \bar{A}^T = \underbrace{A A^T \bar{A}}_{(29)=0} \bar{A}^T = 0$ (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 $\vec{x} \cdot \vec{y} = 0 \quad \forall \vec{x} \in V_A, \vec{y} \in V_{\bar{A}}$ (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.

$$\begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \rightarrow \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \\ \hline \hline \hline \end{matrix} \quad (38)$$

$$\begin{matrix} \hline \hline \hline \\ \hline \hline \hline \end{matrix} \rightarrow \begin{matrix} \hline \hline \hline \\ \hline \hline \hline \\ \hline \hline \hline \end{matrix} \quad (39)$$

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

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

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

$\begin{matrix} M \\ \bullet \end{matrix} = \begin{matrix} U & S & V^T \\ \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} \end{matrix} \quad \text{or} \quad \begin{matrix} \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} \end{matrix}$

$\begin{matrix} D \times D' & D \times \tilde{D} & \tilde{D} \times \tilde{D} & \tilde{D} \times D' \end{matrix}$

where

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

$$V^T \in \text{mat}(\tilde{D}, D'; \mathbb{C}) \text{ satisfies } V^T V = \mathbf{1}_{\tilde{D}} \quad (4)$$

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

Remarks:

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

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

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

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' $S_{\alpha} := S_{\alpha\alpha} = \tilde{\sigma}$

- '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^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 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 $\tilde{D} = D \leq D'$:

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

U is unitary: $U^T U = \tilde{D} \begin{matrix} D \\ \text{[Matrix]} \end{matrix} \cdot D \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \tilde{D} \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \mathbb{1}_{\tilde{D}}$ (16)

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

V^T is right isometry: $V^T V = \tilde{D} \begin{matrix} D' \\ \text{[Matrix]} \end{matrix} \cdot D' \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \tilde{D} \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \mathbb{1}_{\tilde{D}}$ (17)

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

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

U is left isometry: $U^T U = \tilde{D} \begin{matrix} D \\ \text{[Matrix]} \end{matrix} \cdot D \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \tilde{D} \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \mathbb{1}_{\tilde{D}}$ (19)

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

V^T is unitary: $V^T V = \tilde{D} \begin{matrix} D' \\ \text{[Matrix]} \end{matrix} \cdot D' \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \tilde{D} \begin{matrix} \tilde{D} \\ \text{[Matrix]} \end{matrix} = \mathbb{1}_{\tilde{D}}$ (20)

(vi) Truncation via SVD

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

evaluated via SVD:

$$= \text{Tr}(V S U^T U S V^T) = \text{Tr}(V S^2 V^T) = \text{Tr}(S^2) \quad (22)$$

$\underbrace{U^T U}_{=1}$
trace is cyclic
 $\underbrace{V^T V}_{=1}$
singular values determine norm

Truncation

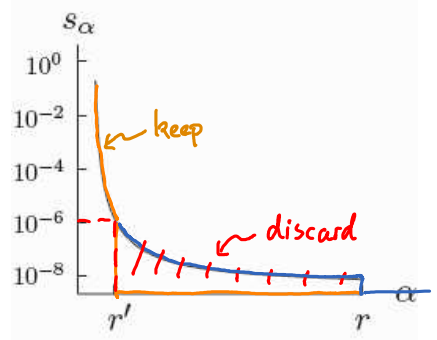
SVD can be used to approximate a rank τ matrix M by a rank $\tau' (< \tau)$ matrix M' :

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

with $S = \text{diag}(s_1, s_2, \dots, s_r, 0, \dots, 0)$ (24)
 $\underbrace{\hspace{10em}}_{\tilde{D} - r \text{ zeros}}$

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

with $S' := \text{diag}(s_1, s_2, \dots, s_{r'}, 0, \dots, 0, \dots, 0)$ (26)
 $\underbrace{\hspace{10em}}_{\tilde{D} - r' \text{ zeros}}$



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

$\tilde{D} = D \leq D'$: $D \begin{matrix} D' \\ M \end{matrix} = D \begin{matrix} \tilde{D} & \tilde{D} \\ | & | \\ | & | \\ | & | \end{matrix} \begin{matrix} \tilde{D} \\ / \\ \backslash \\ / \\ \backslash \end{matrix} \begin{matrix} D' \\ \hline \hline \hline \end{matrix}$ (27)

$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' & & \\ | & & \\ | & 0 & \\ | & & \end{matrix} \begin{matrix} r' & \\ / & \\ \backslash & \\ / & \\ \backslash & \end{matrix} \begin{matrix} D' \\ \hline 0 \\ \hline \hline \end{matrix} = D \begin{matrix} r' & & \\ | & & \\ | & & \end{matrix} \begin{matrix} r' & \\ / & \\ \backslash & \\ / & \\ \backslash & \end{matrix} \begin{matrix} D' \\ \hline \hline \hline \end{matrix}$ (28)
 $\underbrace{\hspace{1em}}_U \quad \underbrace{\hspace{1em}}_{S'} \quad \underbrace{\hspace{1em}}_{V^T} \quad \underbrace{\hspace{1em}}_U \quad \underbrace{\hspace{1em}}_S \quad \underbrace{\hspace{1em}}_{V^T}$

$D \geq D' = \tilde{D}$ $D \begin{matrix} D' \\ M \end{matrix} = D \begin{matrix} \tilde{D} & \tilde{D} \\ | & | \\ | & | \\ | & | \end{matrix} \begin{matrix} \tilde{D} \\ / \\ \backslash \\ / \\ \backslash \end{matrix} \begin{matrix} D' \\ \hline \hline \hline \end{matrix}$ (29)

$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' & & \\ | & & \\ | & 0 & \\ | & & \end{matrix} \begin{matrix} r' & \\ / & \\ \backslash & \\ / & \\ \backslash & \end{matrix} \begin{matrix} D' \\ \hline 0 \\ \hline \hline \end{matrix} = D \begin{matrix} r' & & \\ | & & \\ | & & \end{matrix} \begin{matrix} r' & \\ / & \\ \backslash & \\ / & \\ \backslash & \end{matrix} \begin{matrix} D' \\ \hline \hline \hline \end{matrix}$ (30)
 $\underbrace{\hspace{1em}}_U \quad \underbrace{\hspace{1em}}_{S'} \quad \underbrace{\hspace{1em}}_{V^T} \quad \underbrace{\hspace{1em}}_U \quad \underbrace{\hspace{1em}}_S \quad \underbrace{\hspace{1em}}_{V^T}$

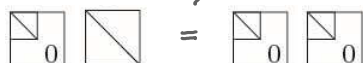
SVD truncation yields 'optimal' approximation of a rank τ matrix M by a rank $\tau' (< \tau)$ matrix M' , in the sense that it can be shown to minimize the Frobenius norm of the difference, $\|M - M'\|_F$.

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

similar steps as for (8)

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

$\underbrace{S' \cdot S}_{= S' \cdot S'} - \underbrace{S \cdot S'}_{= S \cdot S'}$



'discarded weight'

$$\begin{aligned}
 & \begin{array}{|c|c|} \hline \square & \square \\ \hline 0 & \square \\ \hline \end{array} = \begin{array}{|c|c|} \hline \square & \square \\ \hline 0 & 0 \\ \hline \end{array} \\
 & = \text{Tr} (S^2 - S'^2) = \sum_{\alpha=1}^r s_{\alpha}^2 - \sum_{\alpha=1}^{r'} s_{\alpha}^2 = \sum_{\alpha=r'+1}^r s_{\alpha}^2 \quad (33)
 \end{aligned}$$

'discarded weight'

Note:

$$u u^{\dagger} M v v^{\dagger} = u u^{\dagger} U S V^{\dagger} v v^{\dagger} = u s v^{\dagger} = M'$$

(vi) Polar decomposition of square matrix

Any square matrix can be factored into a Hermitian, positive matrix and a unitary matrix: no negative eigenvalues

$$M = U S V^{\dagger} = \begin{cases} (U S U^{\dagger})(U V^{\dagger}) = P W & \text{'left polar decomposition'} \\ (U V^{\dagger})(V S V^{\dagger}) = \tilde{W} \tilde{P} & \text{'right polar decomposition'} \end{cases} \quad (34)$$

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'

$$\begin{aligned}
 D \leq D': \quad D \begin{array}{|c|} \hline D' \\ \hline \end{array} &= D \begin{array}{|c|c|} \hline D & D' \\ \hline \end{array} \\
 M &= Q \quad R \\
 D \geq D': \quad D \begin{array}{|c|} \hline D' \\ \hline \end{array} &= D \begin{array}{|c|c|} \hline D & D' \\ \hline \end{array}
 \end{aligned}$$

$$M = QR \quad (35)$$

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

$$Q Q^{\dagger} = Q^{\dagger} Q = \mathbf{1} \quad (36)$$

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

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

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

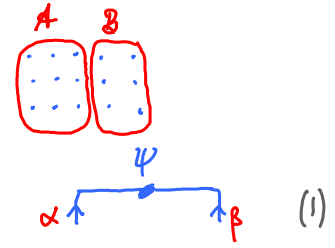
$$Q_1^{\dagger} Q_1 = \mathbf{1} \quad \text{but} \quad Q_1 Q_1^{\dagger} \neq \mathbf{1} \quad (39)$$

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

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

MPS-III.4

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



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

Reduced density matrices of subsystems A and B :

$$\hat{\rho}_A = \text{Tr}_B |\psi\rangle\langle\psi| = \sum_{\alpha', \alpha} |\alpha\rangle_A \langle\alpha'| \psi^{\alpha\alpha'} \langle\alpha'|, \quad (\rho_A)^{\alpha\alpha'} = (\psi\psi^\dagger)^{\alpha\alpha'} \quad \begin{matrix} \uparrow \alpha' \\ \uparrow \alpha \end{matrix} \quad (2)$$

$$\hat{\rho}_B = \text{Tr}_A |\psi\rangle\langle\psi| = \sum_{\beta', \beta} |\beta\rangle_B \langle\beta'| \psi^{\beta\beta'} \langle\beta'|, \quad (\rho_B)^{\beta\beta'} = (\psi^\dagger\psi)^{\beta\beta'} \quad \begin{matrix} \uparrow \beta' \\ \uparrow \beta \end{matrix} \quad (3)$$

Singular value decomposition

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

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

With indices: $\psi^{\alpha\beta} = U^{\alpha\lambda} S^{\lambda\lambda'} V^{\lambda'\beta}$

The diagram shows the tensor network for $\psi^{\alpha\beta} = U^{\alpha\lambda} S^{\lambda\lambda'} V^{\lambda'\beta}$. The S tensor is diagonal, labeled $\text{diag}(s_1, s_2, \dots)$.

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

where $|\lambda\rangle_A = |\alpha\rangle U^{\alpha\lambda}$, $|\lambda\rangle_B = |\beta\rangle V^{\lambda\beta}$

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)

$$\langle \lambda' | \lambda \rangle_A = \begin{matrix} \uparrow \lambda \\ \alpha \uparrow \\ \uparrow \alpha' \\ \uparrow \lambda' \end{matrix} U^\dagger U = U^{\dagger\lambda'} U^{\alpha\lambda} = \mathbb{1}^{\lambda'\lambda} = \begin{matrix} \uparrow \lambda \\ \uparrow \lambda' \end{matrix} \quad (9)$$

$$\langle \lambda' | \lambda \rangle_B = \begin{matrix} \lambda \leftarrow \\ \lambda' \leftarrow \\ \uparrow \beta \\ \uparrow \beta' \end{matrix} V^\dagger V = V^{\dagger\lambda'} V^{\lambda\beta} = \mathbb{1}^{\lambda'\lambda} = \begin{matrix} \uparrow \lambda \\ \uparrow \lambda' \end{matrix} \quad (10)$$

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: $|\psi\rangle = |1\rangle_B |1\rangle_A$. If $r \geq 1$: '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, $s_{\lambda} = r^{-1/2} \quad (16)$

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

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

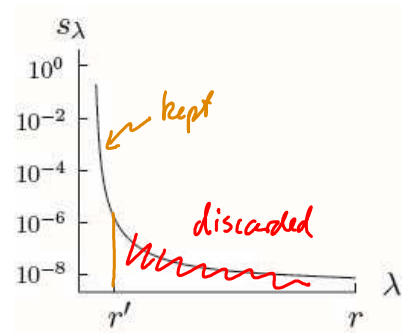
Define truncated state using r' ($< r$) singular values:

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

If $|\tilde{\psi}\rangle$ should be normalized, rescale, i.e. replace s_{λ} by $s_{\lambda} \left[\sum_{\lambda=1}^{r'} (s_{\lambda})^2 \right]^{-1/2} \quad (19)$

Truncation error:

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



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

The truncation strategy (18) minimizes the truncation error.

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