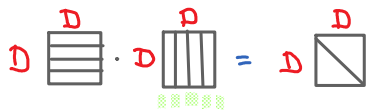
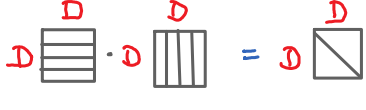


1. Unitaries and isometries (reminder)

Unitaries

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

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



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

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

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

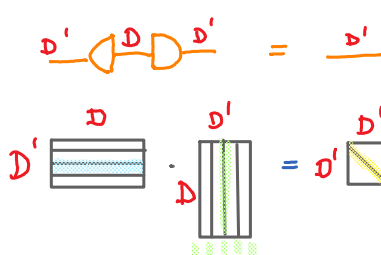
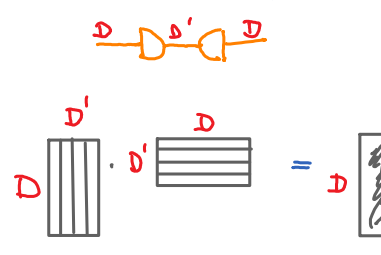
Its inverse is given by

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

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

Left isometry (isometry = distance-preserving map)

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

$$A^\dagger A = \mathbb{1}_{D'} \quad (6a) \quad \text{Then} \quad A A^\dagger \neq \mathbb{1}_D \quad (6b)$$



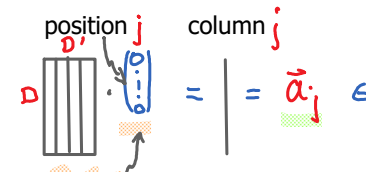
Its D' column vectors, $A = (\vec{a}_1, \vec{a}_2, \dots, \vec{a}_{D'})$, are orthonormal, $\vec{a}_i^\dagger \cdot \vec{a}_j = \delta_{ij} \quad (7)$

They form a basis for a D' -dimensional subspace of \mathbb{R}^D

They form a basis for a D' -dimensional subspace of \mathbb{C}^D ,
 say $V_A = \text{span}\{\bar{a}_1, \bar{a}_2, \dots, \bar{a}_{D'}\} \subsetneq \mathbb{C}^D$ space of D -dimensional column vectors (9)

$$\bar{a}_i^t = \bar{a}_i^T$$

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

Formally:
 $A: \mathbb{C}^{D'} \rightarrow \mathbb{C}^D$, $\bar{f}_j \mapsto A\bar{f}_j := \bar{e}_i A_{ij} = \bar{a}_j$ $j \in 1, \dots, D'$ (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 $A: \mathbb{C}^{D'} \rightarrow \mathbb{C}^D, \bar{x} \mapsto \bar{y} = A\bar{x}$, then

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

Left projector

$$D \xrightarrow{A} D' \xrightarrow{A^t} D = P = A A^t = \begin{matrix} D' \\ \text{matrix} \end{matrix} \cdot \begin{matrix} D \\ \text{matrix} \end{matrix} = \begin{matrix} D \\ \text{shaded box} \end{matrix}$$
 (11)

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



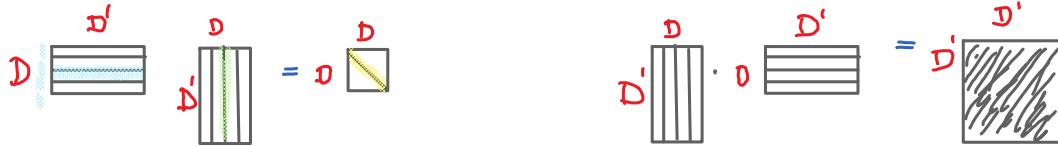
Its action leaves V_A invariant, because it leaves each its basis vectors invariant: (13)

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

Right isometry

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

$$B B^\dagger = \mathbb{1}_D \quad (14a) \quad \text{Then} \quad B^\dagger B \neq \mathbb{1}_{D'} \quad (14b)$$



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]

They form a basis for a D -dimensional subspace of $\mathbb{C}^{*D'}$, space of D' -dimensional row vectors

say $V_B^* = \text{span}\{\vec{b}^1, \vec{b}^2, \dots, \vec{b}^D\} \subsetneq \mathbb{C}^{*D'}$ (16)

subspace

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

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

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

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

short row vectors long row vectors

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

$i \in 1, \dots, D'$
 $j \in 1, \dots, D$

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

These span $V_B^* \subsetneq \mathbb{C}^{*D}$, the 'image space of B ' or 'image of B ', with dimension $\dim(B) = D'$.
 because 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

$$\begin{matrix} D' & D & D' \\ \hline \rightarrow & \rightarrow & \rightarrow \\ \hline \end{matrix} = P = B^T B = \begin{matrix} D \\ \hline \end{matrix} \cdot \begin{matrix} D' \\ \hline \end{matrix} = \begin{matrix} D' \\ \hline \end{matrix} \quad (19)$$

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

$$\begin{matrix} \rightarrow & \rightarrow & \rightarrow & \rightarrow \\ \hline \end{matrix} = \begin{matrix} \rightarrow & \rightarrow \\ \hline \end{matrix}$$

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

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

Truncation of unitaries yield isometries

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

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

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

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

Unitarity of U implies:

$$\begin{pmatrix} \mathbb{1}_{D'} & \\ & \mathbb{1}_{\bar{D}'} \end{pmatrix} = \mathbb{1}_D = U^T U = \begin{pmatrix} A^T \\ \bar{A}^T \end{pmatrix} (A, \bar{A}) = \begin{pmatrix} A^T A & A^T \bar{A} \\ \bar{A}^T A & \bar{A}^T \bar{A} \end{pmatrix} \quad (25)$$

$$\begin{matrix} \square & \square \\ \hline \square & \square \end{matrix} = \begin{matrix} \square \\ \hline \square \end{matrix} = \begin{matrix} D' & \bar{D}' \\ \hline \end{matrix} \cdot \begin{matrix} D' & \bar{D}' \\ \hline \end{matrix} \quad (26)$$

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

$$\begin{matrix} D & D' \\ \hline \end{matrix} = A^T A \stackrel{(25)}{=} \mathbb{1}_{D'} \quad , \quad \begin{matrix} \bar{D}' & \bar{D}' \\ \hline \end{matrix} = \bar{A}^T \bar{A} \stackrel{(25)}{=} \mathbb{1}_{\bar{D}'} \quad (27)$$

$$\begin{matrix} D' & D \\ \hline \end{matrix} \cdot \begin{matrix} D' \\ \hline \end{matrix} = \begin{matrix} D' & D' \\ \hline \end{matrix} \quad , \quad \begin{matrix} D & \bar{D}' \\ \hline \end{matrix} \cdot \begin{matrix} \bar{D}' \\ \hline \end{matrix} = \begin{matrix} \bar{D}' & \bar{D}' \\ \hline \end{matrix}$$

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

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

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

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

Complementary projectors

The projectors, $P = A A^+ = \begin{matrix} D & D' \\ \hline D & \bar{D}' \end{matrix}, \quad \bar{P} = \bar{A} \bar{A}^+ = \begin{matrix} D & \bar{D}' \\ \hline D & \bar{D}' \end{matrix} \quad (31)$

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.: $P \cdot \bar{P} = A A^+ \bar{A} \bar{A}^+ \stackrel{(29)}{=} 0 = 0 \quad (34)$

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

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

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

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

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.

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 (without proof)

$$M = U \cdot S \cdot V^T \quad \begin{matrix} M \\ \bullet \end{matrix} = \begin{matrix} U & S & V^T \\ \text{---} & \text{---} & \text{---} \end{matrix} \quad (2)$$

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

where

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

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

$S \in \text{mat}(\tilde{D}, \tilde{D}; \mathbb{C})$ is diagonal, with purely non-negative diagonal elements. (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, columns of U are eigenvectors of MM^T , and columns of V are eigenvectors of $M^T M$.

(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)

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)

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

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

Truncation

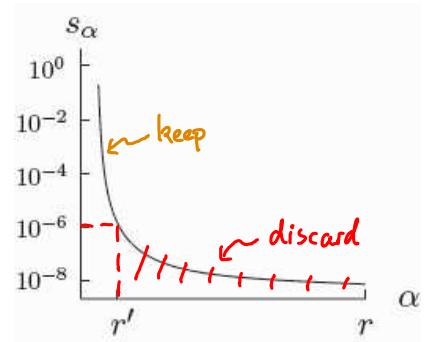
SVD can be used to approximate a rank τ matrix M by a rank $\tau' (< \tau)$ matrix M' :

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

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

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

$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} | & | & | \\ | & 0 & \\ | & & \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} / \\ \backslash \\ 0 \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{---} \\ \text{---} \\ 0 \end{matrix} \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} | \\ | \\ | \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} / \\ \backslash \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{---} \\ \text{---} \\ \text{---} \end{matrix} \end{matrix}$ (28)
 U S' V^T u s v^T

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

$D \begin{matrix} D' \\ M' \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} | & | & | \\ | & 0 & \\ | & & \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} / \\ \backslash \\ 0 \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{---} \\ \text{---} \\ 0 \end{matrix} \end{matrix} = D \begin{matrix} r' \\ \begin{matrix} | \\ | \\ | \end{matrix} \end{matrix} \begin{matrix} r' \\ \begin{matrix} / \\ \backslash \end{matrix} \end{matrix} \begin{matrix} D' \\ \begin{matrix} \text{---} \\ \text{---} \\ \text{---} \end{matrix} \end{matrix}$ (30)
 u s 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, $\|M - M'\|_F$.

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

similar steps as for (8)
 $= \text{Tr} (\underbrace{S \cdot S}_{=S \cdot S} + \underbrace{S' \cdot S'}_{=S' \cdot S'} - \underbrace{S' \cdot S}_{=S' \cdot S} - \underbrace{S \cdot S'}_{=S \cdot S'})$ (32)

$$\begin{aligned}
 & \begin{array}{|c|c|} \hline \square & \square \\ \hline 0 & \square \\ \hline \end{array} = \begin{array}{|c|c|} \hline \square & \square \\ \hline 0 & \square \\ \hline \end{array} \\
 & = \text{Tr} \left(S^2 - S'^2 \right) = \sum_{\alpha=1}^r s_{\alpha}^2 - \sum_{\alpha=1}^{r'} s_{\alpha}^2 = \sum_{\alpha=r'+1}^r s_{\alpha}^2 \quad (33) \\
 & \hspace{15em} \text{'discarded weight'}
 \end{aligned}$$

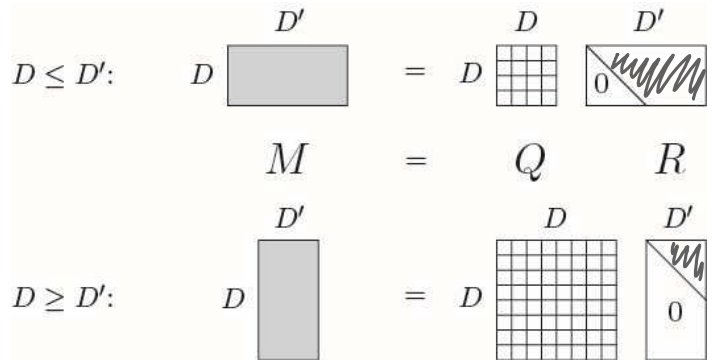
QR-decomposition

If singular values are not needed,

a $D \times D'$ matrix M

has the 'full QR decomposition'

$$M = QR \quad (14)$$



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

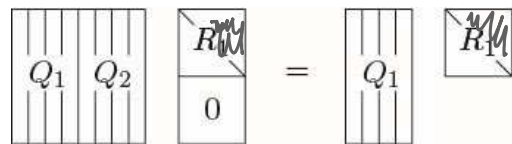
$$QQ^{\dagger} = Q^{\dagger}Q = \mathbf{1} \quad (29)$$

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

$$R_{\alpha\beta} = 0 \text{ if } \alpha > \beta \quad (30)$$

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

$$M = (Q_1, Q_2) \cdot \begin{pmatrix} R_1 \\ 0 \end{pmatrix} = Q_1 \cdot R_1 \quad (13)$$



with $\dim(Q_1) = D \times D'$, $\dim(R_1) = D' \times D'$,

$$Q_1^{\dagger} Q_1 = \mathbf{1} \text{ but } Q_1 Q_1^{\dagger} \neq \mathbf{1} \quad (31)$$

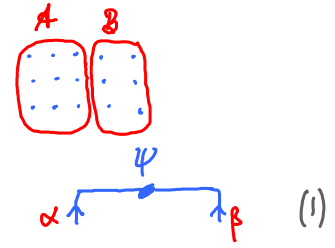
and R_1 upper triangular.

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

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

MPS-III.3

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



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

Reduced density matrices of subsystems A and B :

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

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

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:

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

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

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

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

$$\langle\lambda'|\lambda\rangle_A = u^\dagger_{\alpha\lambda'} u_{\alpha\lambda} = \mathbb{1}^{\lambda'\lambda} = \begin{cases} 1 \\ \lambda' \end{cases} \quad (9)$$

$$\langle\lambda'|\lambda\rangle_B = v^\dagger_{\lambda'\beta} v_{\lambda\beta} = \mathbb{1}_{\lambda\lambda'} = \begin{cases} \lambda \\ \lambda' \end{cases} \quad (10)$$

Restrict \sum_λ to the r non-zero singular values:

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

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

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

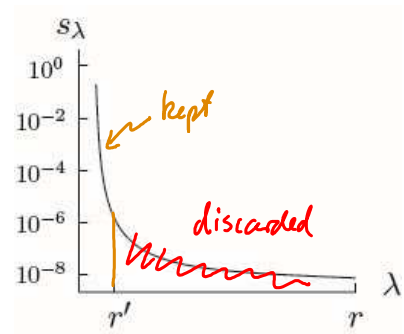
Define truncated state using r' ($< r$) singular values:

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

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:

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



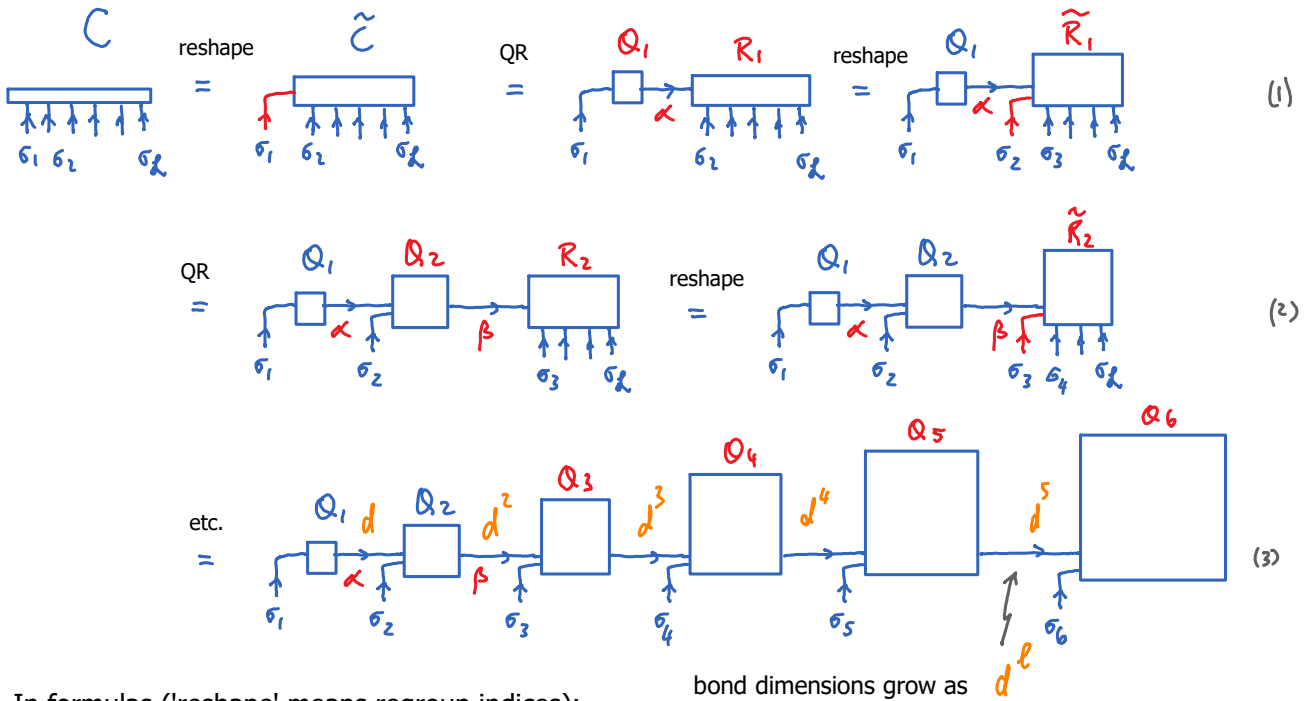
Useful to obtain 'cheap' representation of $|\psi\rangle$ if singular values decay rapidly.

The truncation strategy (18) minimizes the truncation error.

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

4. Reshaping generic tensor into MPS form

A generic tensor of arbitrary rank can be expressed as an MPS by repeatedly performing SVDs.



In formulas ('reshape' means regroup indices):

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

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

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

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

$$R \stackrel{\text{SVD}}{=} U S V^t \stackrel{\text{truncate}}{\approx} u s v^t \quad \text{where } S \text{ contains only largest } D \text{ singular values of } R$$

