

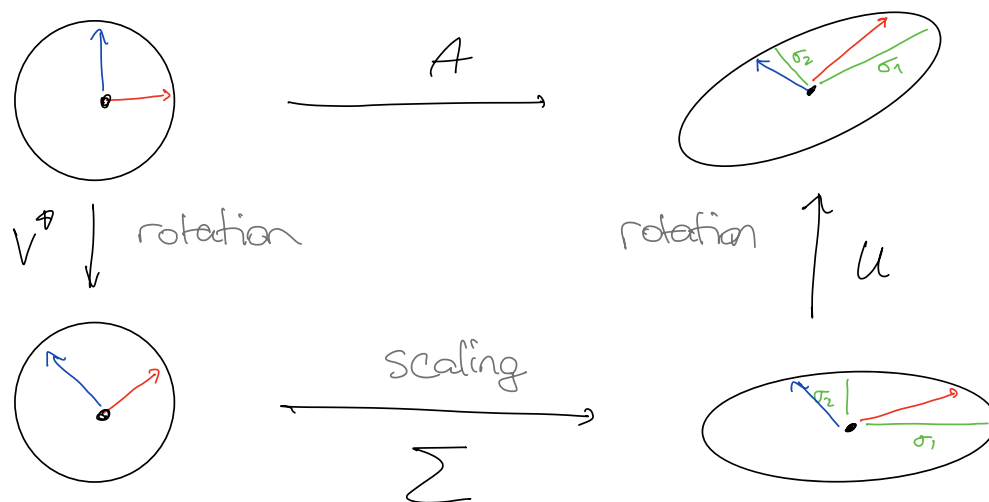
# The singular value decomposition (SVD)

→ cornerstone of linear algebra

$$A = U \cdot \Sigma \cdot V^{\dagger}$$

$\uparrow$  unitary       $\uparrow$  diagonal with non-negative entries       $\uparrow$  unitary

→ nice geometrical interpretation.



## The SVD

There exist

$$A \in \mathcal{M}_{m \times n}(\mathbb{C}) \quad r := \text{rank}(A)$$

- $U \in \mathcal{U}(m)$  columns of  $U$ : left sing. vectors
- $V \in \mathcal{U}(n)$  columns of  $V$ : right singular vectors
- $\Sigma \in \mathcal{M}_{m \times n}$  "diagonal"

singular values  
 $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$

$$\Sigma = \begin{matrix} & \begin{matrix} \sigma_1 & \sigma_2 & \dots & \sigma_r & 0 & \dots & 0 \end{matrix} \\ \begin{matrix} m \\ n \end{matrix} & \begin{bmatrix} \sigma_1 & & & & & & \\ & \sigma_2 & & & & & \\ & & \dots & & & & \\ & & & \sigma_r & & & \\ & & & & 0 & \dots & 0 \end{bmatrix} \end{matrix}$$

$$\forall i \leq \min(m, n) \quad \sum_{ii} = \sigma_i$$

$$\sigma_{r+1} = \dots = \sigma_{\min(m, n)} = 0$$

$$i \neq j \quad \sum_{ij} = 0$$

Such that  $A = U \Sigma V^\dagger$

- In bra-ket notation

$$A = \sum_{i=1}^{\min(m, n)} \sigma_i |u_i\rangle \langle v_i|$$

$$U = \sum_{i=1}^m |u_i\rangle \langle i| \quad V = \sum_{j=1}^n |v_j\rangle \langle j|$$

$$U \Sigma V^\dagger = \sum_{ij} |u_i\rangle \langle v_j| \cdot \sum_{ij}$$

$$= \sum_i \sigma_i |u_i\rangle \langle v_i|$$

- In graphical notation:

$$\boxed{A} = \boxed{U \Sigma V^\dagger} = \boxed{U} \boxed{\Sigma} \boxed{V^\dagger}$$

$\Sigma$  diagonal

$$\boxed{\Sigma} \stackrel{i=j}{=} \boxed{\Sigma}$$

$$\boxed{\Sigma} \stackrel{i=j}{=} \text{dot} = \delta_{ij} \cdot \sigma_i$$

- "reduced" SVD : only keep the s.v.  $> 0$

$$A = \underbrace{{}_m \tilde{U}_r \text{diag}(\sigma_1, \dots, \sigma_r)}_{r \times r \text{ matrix}} \tilde{V}_n^\dagger$$

$$\begin{aligned}\tilde{U} &: \mathbb{C}^r \rightarrow \mathbb{C}^m \\ \tilde{V} &: \mathbb{C}^r \rightarrow \mathbb{C}^n\end{aligned} \quad \left\{ \begin{array}{l} \text{isometries} \end{array} \right.$$

$$U = \sum_{i=1}^r |u_i\rangle\langle X_i| \quad \tilde{U} = \sum_{i=1}^r |u_i\rangle\langle X_i|$$

$$U = \begin{array}{c} \underbrace{\quad}_{r \text{ rows}} \\ \begin{array}{|c|} \hline \tilde{U} \\ \hline \end{array} \\ n \end{array}$$

graphical SVD:

$$\begin{array}{c} m \\ \boxed{A} \\ n \end{array} = \begin{array}{c} m \\ \boxed{U} \end{array} \begin{array}{c} m \\ \boxed{\Sigma} \end{array} \begin{array}{c} n \\ \boxed{V^*} \end{array}$$

$$\begin{array}{c} m \\ \boxed{A} \\ n \end{array} = \begin{array}{c} m \\ \boxed{\tilde{U}} \end{array} \begin{array}{c} r \\ \text{---} \end{array} \begin{array}{c} n \\ \boxed{\tilde{V}^*} \end{array}$$

Sometimes  $\tilde{U}: \mathbb{C}^r \rightarrow \mathbb{C}^m$  isometry

$$\begin{array}{c} m \\ \triangleleft \tilde{U} \end{array} \begin{array}{c} r \end{array} \quad \text{or} \quad \begin{array}{c} m \\ \triangleleft \tilde{U} \end{array} \begin{array}{c} r \end{array}$$

$$\tilde{U}^* \tilde{U} = I_r \quad \begin{array}{c} r \\ \triangleleft \tilde{U}^* \end{array} \begin{array}{c} m \\ \triangleleft \tilde{U} \end{array} = \begin{array}{c} r \end{array}$$

### Uniqueness of the SVD

- the numbers  $\sigma_1 \geq \dots \geq \sigma_r > 0$  are unique
- if  $\sigma_1 > \sigma_2 > \dots > \sigma_r$  then  $|u_1\rangle, \dots, |u_r\rangle, |v_1\rangle, \dots, |v_r\rangle$  are unique

up to phases

$$A = \sum \sigma_i |u_i\rangle \langle v_i|$$

phases

Example

$$I = \sum 1 \cdot |u_i\rangle \langle u_i|$$

for any onb  $\{u_i\}$

"Uniqueness"  $\Rightarrow$  # parameters of  $A =$

# parameters of  $\{\sigma, u, v\}$

# real parameters of  $A \in \mathcal{M}_n(\mathbb{C}) = 2n^2$

# parameters  $(\sigma, U, V)$

$n : (\sigma_1, \dots, \sigma_n)$

# parameters in  $U \in U(n)$

$$U = \begin{array}{c|c|c} \begin{array}{c} 2 \\ 2 \\ \vdots \\ 2 \\ 1 \end{array} & \begin{array}{c} \sigma \\ 1 \\ \vdots \\ \sigma \end{array} & \begin{array}{c} \leftarrow \langle u_1, v_1 \rangle = 0 \\ \leftarrow \|u_2\| = 1 \end{array} \\ \hline \begin{array}{c} 2n-1 \\ 2n-3 \\ \vdots \\ 1 \end{array} & \begin{array}{c} 2n-3 \\ 2n-5 \\ \vdots \\ 1 \end{array} & n \end{array}$$

$$n=2 : 3+1=4$$

$$n=3 : 5+3+1=9$$

$$U_3 : 2n-1 - \underset{\text{norm}}{2} \cdot \underset{\substack{\uparrow \\ \perp \text{ to } u_1 \text{ and } u_2}}{2} = 2n-5$$

$$\begin{aligned} \text{In general : } \dim_{\mathbb{R}} U(n) &= \sum_{i=1}^n 2n - (2i-1) = n^2 \\ &= 2n^2 - 2 \frac{n(n+1)}{2} + n \end{aligned}$$

$$\dim_{\mathbb{R}} \mathcal{U}(n) = n^2$$

OR :  $\dim_{\mathbb{R}} \mathcal{U}(n) = \dim_{\mathbb{R}} \text{its Lie algebra}$   
 $\quad \quad \quad \uparrow$   
 $\quad \quad \text{Lie group} \quad = \dim_{\mathbb{R}} \text{skew-sym. mat}$   
 $\quad \quad \quad = n^2$

# params of  $(\sigma, U, V)$  phases  $|u_i\rangle, |v_i\rangle$   
 $n + n^2 + n^2 - n = 2n^2$

$$(U, V) \in \mathcal{U}(d) / \mathcal{U}(1)^N \times \mathcal{U}(d) / \mathcal{U}(1)^N \times \mathcal{U}(1)^N$$

no phase in columns  
i.e.  $U = \begin{bmatrix} \cdot & \cdot & \cdot \\ \cdot & * \end{bmatrix}$  ← real numbers

How about tensor SVD ?

$$\left\{ \begin{array}{l} T \in \mathbb{C}^n \otimes \mathbb{C}^n \otimes \mathbb{C}^n \\ \# \text{ params} = 2n^3 \end{array} \right. \quad \left. \begin{array}{l} \text{general} \\ \text{tensors} \end{array} \right\}$$

of order  $n^3$

$$\left\{ \begin{array}{l} \text{SVD-able tensors} \\ T = \sum_i \sigma_i |u_i\rangle \otimes |v_i\rangle \otimes |w_i\rangle \\ \sigma_i \geq 0 \\ \{u_i\}, \{v_i\}, \{w_i\} \text{ o.n.b.} \\ \# \text{ params} = 3n^2 - n \end{array} \right.$$

of order  $n^2$

SVD-able tensors in  $(\mathbb{C}^n)^{\otimes k}$

form a manifold of  $\dim_{\mathbb{R}} \sim k \cdot n^2$

vs Cat Lergen  $\nearrow$

all tensors in  $(\mathbb{C}^n)^{\otimes k}$   $\dim_{\mathbb{R}} = 2n^k$

### Back to matrices

SVD:  $A = U \Sigma V^\dagger$   $\leftrightarrow$  general matrices, even rectangular

eigenvalue decomposition

$A = A^\dagger$  (hence square)

$$A = W \cdot \Lambda \cdot W^\dagger$$

$\nearrow$  eigenvectors       $\nwarrow$  eigenvalues

$$A = \sum \lambda_i |w_i\rangle\langle w_i|$$

$$\Lambda = \text{diag}(\lambda) = \sum \lambda_i |i\rangle\langle i|$$

$$W = \sum |w_i\rangle\langle i|$$

Relation between SVD and eig. decomp

$$A = U \Sigma V^\dagger \Rightarrow AA^\dagger = U \Sigma V^\dagger V \Sigma U^\dagger$$

$$= U \underbrace{\Sigma^2}_{\text{diag}(\sigma_i^2)} U^\dagger$$

$$\Rightarrow \begin{cases} \sigma_i \text{'s are } \sqrt{\text{eigs of } AA^\dagger} \\ U_i \text{'s are the eig of } AA^\dagger \\ V_i \text{'s are the eig of } A^\dagger A \end{cases}$$

This is how you compute the SVD!

- polar decomposition  $A = W \cdot P$   
 $\begin{matrix} \nearrow & \nwarrow \\ \text{unitary} & \text{positive} \\ & \text{semidefinite} \end{matrix}$

(matrix version of  $z = e^{i\theta} \cdot |z|$ )

→ unique, up to degeneracies

$$\begin{aligned} A &= U \Sigma V^\dagger \\ &= \underbrace{U V^\dagger}_W \underbrace{V \Sigma V^\dagger}_P \end{aligned}$$

$P$  is positive semidef. since it has eigs  $\sigma_i$ 's

### Schmidt decomposition for q. states

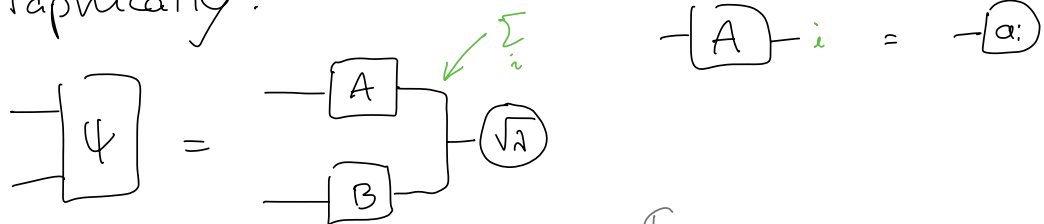
Any  $|\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$  can be decomposed as

$$|\psi\rangle = \sum_i \sqrt{\lambda_i} |a_i\rangle \otimes |b_i\rangle$$

where

- $\lambda_i \geq 0$ ,  $\sum \lambda_i = 1$  Schmidt coefficients
- $\{a_i\}, \{b_i\}$  o.n.b. of  $\mathbb{C}^d$ .

graphically:



Remark

$$\begin{aligned} |\psi\rangle &= \sum_{ij} \psi_{ij} |i\rangle \otimes |j\rangle \\ &= \sum_{ij} |\psi_{ij}| e^{i \arg(\psi_{ij})} |i\rangle \otimes |j\rangle \end{aligned}$$

2 indices

$$\begin{array}{c} \text{---} \boxed{\psi} \text{---} \\ \text{---} \end{array} = \begin{array}{c} \text{---} \boxed{A} \text{---} \\ \text{---} \boxed{B} \text{---} \end{array} \text{---} (\sqrt{\lambda}) \quad (\Rightarrow) \quad \begin{array}{c} \text{---} \boxed{\psi} \text{---} \\ \text{---} \end{array} = \begin{array}{c} \text{---} \boxed{A} \text{---} \\ \text{---} \end{array} \text{---} (\sqrt{\lambda}) \text{---} \boxed{B^T} \text{---}$$

This is the SVD  
of  $\boxed{\psi}$

$$\text{---} \boxed{\text{vec}(X)} \text{---} = \text{---} \boxed{X} \text{---}$$

matrix

= anti-vectorization  
of  $|\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$

$$\text{---} \boxed{\text{anti-vec}(|\psi\rangle)} \text{---} = \text{---} \boxed{\psi} \text{---}$$

Remark

$$\begin{array}{c} \text{---} \boxed{\psi} \text{---} \\ \text{---} \end{array} \rightsquigarrow |\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$$

thick wire  $\rightsquigarrow d^2$

$$\begin{array}{c} \text{---} \boxed{\psi} \text{---} \\ \text{---} \end{array} = \text{---} \boxed{\tilde{\psi}} \text{---} \quad |\tilde{\psi}\rangle \in \mathbb{C}^{d^2}$$

$\Rightarrow$  the Schmidt coeffs  $\lambda_i$  are the squared s.v.

$$\lambda_i = \sigma_i^2$$

The partial traces of  $|\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$

$$\rho_1 = \text{Tr}_2 |\psi\rangle\langle\psi|$$

$$= \text{Tr}_2 \left( \sum_{ij} \sqrt{\lambda_i} \sqrt{\lambda_j} |a_i\rangle |b_i\rangle \langle a_j| \langle b_j| \right)$$

$$= \sum_{ij} \sqrt{\lambda_i \lambda_j} |a_i\rangle \langle a_j| \underbrace{\text{Tr}(|b_i\rangle\langle b_j|)}_{\delta_{ij}}$$



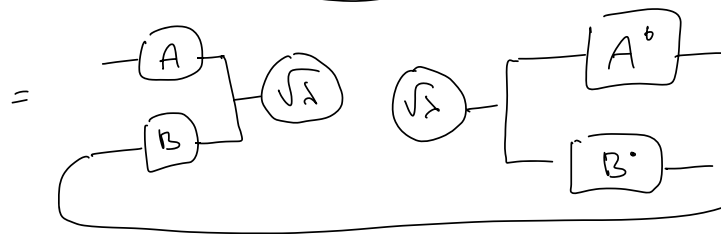
$$= \sum \lambda_i |a_i \rangle \langle a_i| \quad \text{eigenvalue decomp of } \rho_1$$

$$\left( \text{Tr } \rho_1 = \sum \lambda_i = 1 \right)$$

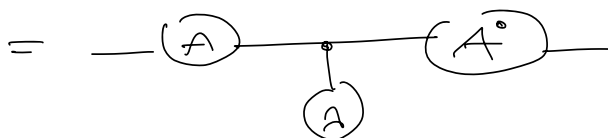
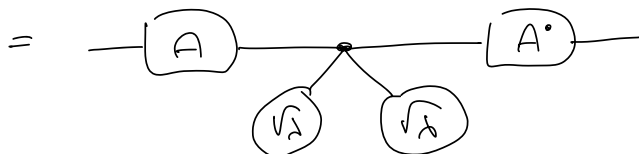
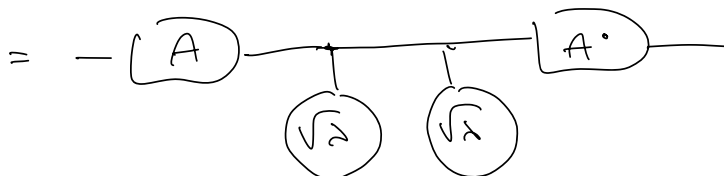
Similarly  $\rho_2 = \sum_i \lambda_i |b_i \rangle \langle b_i|$

Graphically

$$[\rho_1] = [\psi] [\psi]$$

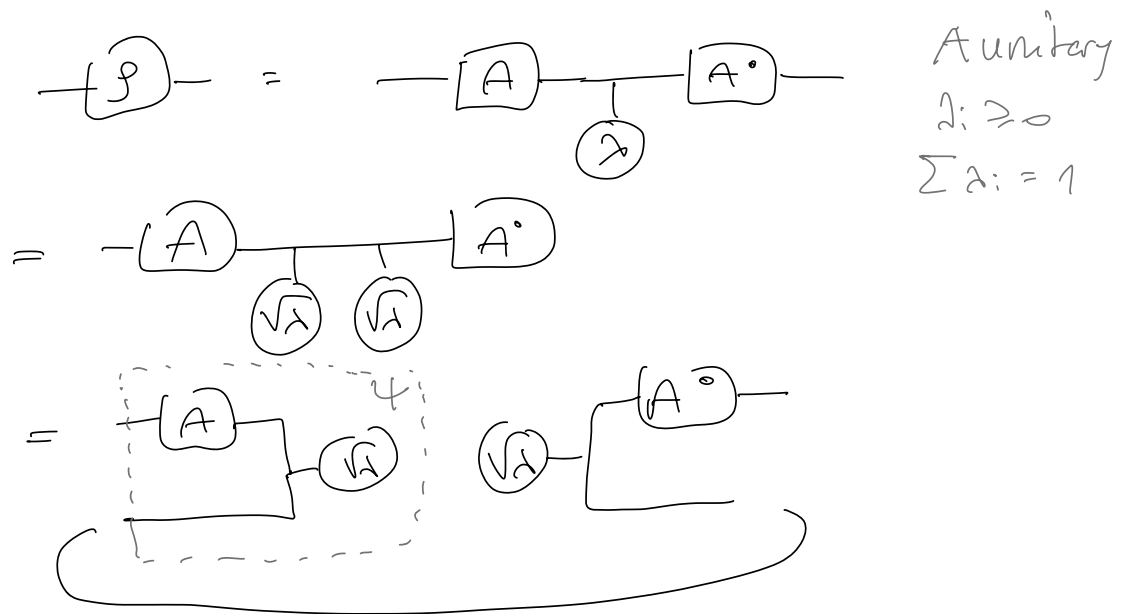


slide B's  
and use  
unitarity



Purification for any density matrix  $\rho$   
 $\exists \psi_{1,2}$  pure s.t.  $\text{Tr}_2 |\psi \rangle \langle \psi| = \rho$

$\rho$  density matrix  $\Rightarrow \rho = \sum \lambda_i |a_i \rangle \langle a_i|$



## The Eckart - Young - Mirsky theorem

$A \in \mathcal{M}_n(\mathbb{C})$  a matrix

Question Given  $r < n$ , what is the best rank- $r$  approximation of  $A$ ?

Best?

$$\min_{B: \text{rank } B \leq r} \|A - B\|$$

What norm / distance?

- operator norm / spectral norm

$$\|A\|_{\infty} = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$$

• euclidean norm / Frobenius norm

$$\|A\|_2 = \sqrt{\sum_{i,j} |A_{ij}|^2} = \|\text{vec}(A)\|$$

$$= \text{Tr}(A^*A)$$

$$\|A\|_\infty = \max_i \sigma_i = \sigma_1$$

$$\|A\|_2 = \|\sigma\| = \sqrt{\sum_{i=1}^n \sigma_i^2}$$

EYM theorem

$$\min_{\text{rank } B \leq r} \|A - B\|_\infty = \sigma_{r+1}$$

$$\min_{\text{rank } B \leq r} \|A - B\|_2 = \sqrt{\sum_{i=r+1}^n \sigma_i^2}$$

SVD truncated  
to its first  $r$  terms

$$\text{In both cases, } B = \sum_{i=1}^r \sigma_i |a_i\rangle\langle b_i|$$

achieves the minimum.