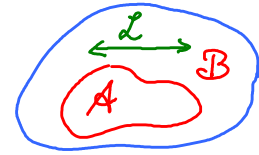


1. Entanglement Entropy and Area Laws

Consider quantum system in state $|\psi\rangle$, with density matrix $\hat{\rho} = |\psi\rangle\langle\psi|$

Divide system into two parts, A and B . Suppose A has linear dimension L .



To obtain reduced density matrix of A (or B), trace out B (or A):

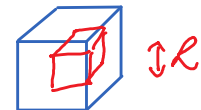
'reduced density matrix' for A : $\hat{\rho}_A \equiv \text{Tr}_B \hat{\rho}$ and $\hat{\rho}_B \equiv \text{Tr}_A \hat{\rho}$ (1)

'Entanglement entropy' of A and B : $S_{A/B} = -\text{Tr} \hat{\rho}_A \ln_2 \hat{\rho}_A = -\sum_a w_a \ln_2 w_a$ (2)
eigenvalues of $\hat{\rho}_A$

It turns out: for Hamiltonians with only local interactions, $S_{A/B}$ is governed by an 'area law':

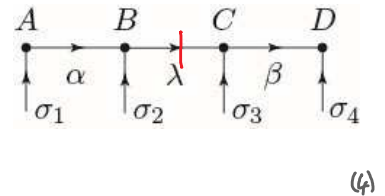
$S^A \equiv S_{A/B} \sim$ (area of boundary of A) $\equiv \partial A$ (3)

- $\sim L^2$ in 3D for gapped system (3a)
- $\sim L$ in 2D for gapped system (3b)
- $\sim \text{const.}$ in 1D for gapped system (3c)
- $\sim \text{const.} + \ln N$ in 1D for gapless system (3d)



Now consider an MPS of maximal bond dimension D:

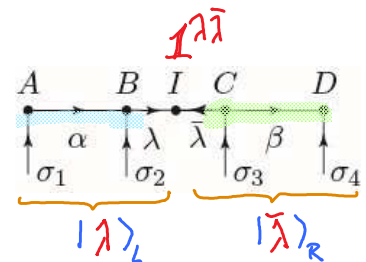
$|\psi\rangle = |\sigma_4\rangle \otimes |\sigma_3\rangle \otimes |\sigma_2\rangle \otimes |\sigma_1\rangle A_{\alpha}^{\sigma_1} B_{\lambda}^{\sigma_2} C_{\tilde{\lambda}}^{\sigma_3} D_{\beta}^{\sigma_4}$
 unit tensor $\equiv \begin{matrix} \uparrow \lambda \tilde{\lambda} \\ \uparrow \tilde{\lambda} \lambda \\ \uparrow \beta \\ \uparrow \alpha \end{matrix} C_{\tilde{\lambda}}^{\sigma_3} D_{\beta}^{\sigma_4}$



divide systems into two parts: Left: 2 sites, Right: 2 sites
system system

$|\psi\rangle = \underbrace{|\tilde{\lambda}\tilde{\lambda}\rangle_R}_{\text{Left}} \otimes \underbrace{|\lambda\lambda\rangle_L}_{\text{Right}} = \sum_{\lambda\tilde{\lambda}} |\tilde{\lambda}\tilde{\lambda}\rangle_R \otimes |\lambda\lambda\rangle_L$ (4)

$|\psi\rangle = \sum_{\lambda\tilde{\lambda}} |\tilde{\lambda}\tilde{\lambda}\rangle_R \otimes |\lambda\lambda\rangle_L$ (5)
 = entangled superposition of two state spaces, each having dimension of at most D



$|\psi\rangle = \sum_{\lambda=1}^D |\lambda\rangle_R \otimes |\lambda\rangle_L$ (6)
suppress \otimes henceforth

(After the sum over $\tilde{\lambda}$ has been performed explicitly using the Kronecker delta, the result contains non-covariantly paired indices.) (7)

Density matrix: $\hat{\rho} = |\psi\rangle\langle\psi| = \sum_{\lambda\lambda'} |\lambda\rangle_R |\lambda\rangle_L \langle\lambda'|_L \langle\lambda'|_R$ (8)

Reduced density matrix: $\hat{\rho}_A = \text{Tr}_B \hat{\rho} = \sum_{\mu} \langle\mu|_R \sum_{\lambda\lambda'} |\lambda\rangle_R |\lambda\rangle_L \langle\lambda'|_L \langle\lambda'|_R |\mu\rangle_R$ (9)

complete set of states for B

$= \sum_{\lambda\lambda'} |\lambda\rangle_L (\rho_A)_{\lambda\lambda'}^A \langle\lambda'|_L$ (10)

with matrix elements

$(\rho_A)_{\lambda\lambda'}^A = \sum_{\mu} \langle\mu|_R \langle\lambda'|_R \rho_R \langle\lambda|_R |\mu\rangle_R = \sum_{\mu} \langle\lambda'|_R \langle\mu|_R \rho_R \langle\lambda|_R = \langle\lambda'|_R \rho_R \langle\lambda|_R = \langle\lambda'|_R \rho_R \langle\lambda|_R$ (11)

This matrix has rank $\leq D$ (say $= D$) (rank = maximum number of linearly independent rows or column)


Let ω_{α} be its eigenvalues, with $\alpha = 1, \dots, D$

and normalization $1 = \text{Tr} \hat{\rho}_A = \sum_{\alpha=1}^D \omega_{\alpha}$ (12)

Entanglement entropy: $S^{(2)} = - \sum_{\alpha=1}^D \omega_{\alpha} \log_2 \omega_{\alpha}$

Maximal if $\omega_{\alpha} = \frac{1}{D}$ for all α : $\leq - \sum_{\alpha=1}^D \frac{1}{D} \log_2 \frac{1}{D} = \log_2 D$ (13)

$\Rightarrow 2^S \leq D$ (14)

1D gapped: $D \stackrel{(3c)}{\sim} 2^{\text{const}}$ (independent of system size!)  (15a)

1D critical: $\stackrel{(3d)}{\sim} 2^{\text{const} + \ln N} \sim \text{power law in } N$  (15b)

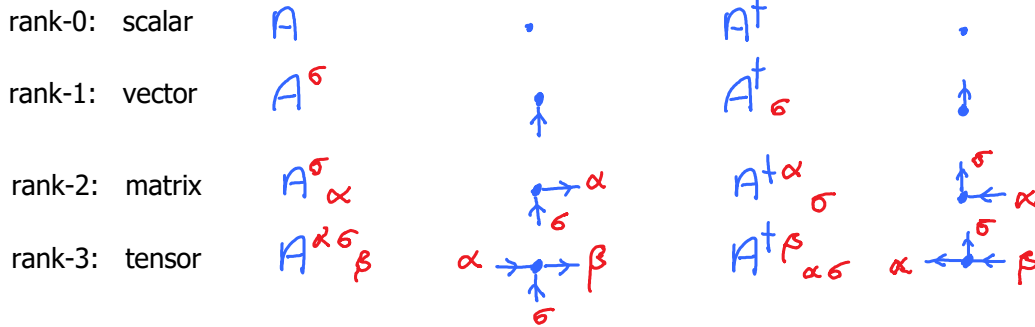
2D gapped: $\stackrel{(3b)}{\sim} 2^L$  (15c)

3D gapped: $\stackrel{(3a)}{\sim} 2^{L^2}$  (15d)

Important conclusion: MPS can encode ground state efficiently for gapped and gapless systems in 1D, but not in 2D or 3D!

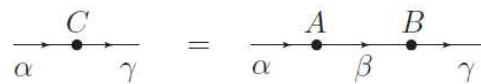
'tensor' = multi-dimensional array of numbers

'rank of tensor' = number of indices = # of legs



Index contraction: summation over repeated index

$$C^\alpha_\beta = \sum_{\gamma=1}^{D_\gamma} A^\alpha_\gamma B^\gamma_\beta \equiv A^\alpha_\gamma B^\gamma_\beta$$



graphical representation of matrix product

D_β = 'bond dimension' of index β

(depends on context, can be different for each index; is often/usually not written explicitly)

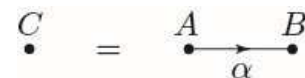
'open index' = non-contracted index (here α, β)

'tensor network' = set of tensors with some or all indices contracted according to some pattern

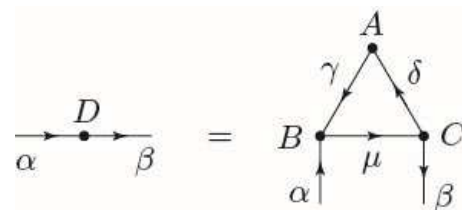
Examples:

$$C = A_\alpha B^\alpha$$

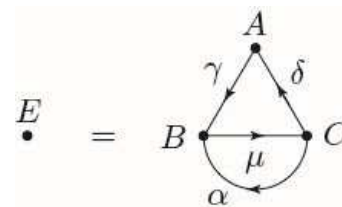
scalar vector \cdot dual vector



$$D^\alpha_\beta = A^\delta_\gamma B^{\gamma\alpha}_\mu C^{\mu\beta}$$

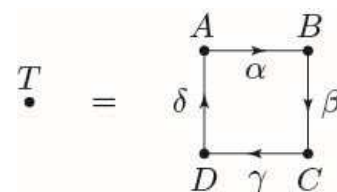


$$E = D^\alpha_\alpha = A^\delta_\gamma B^{\gamma\alpha}_\mu C^{\mu\alpha}$$



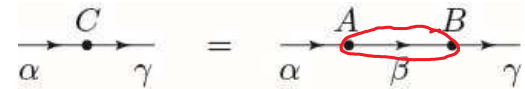
Trace of matrix product:

$$T = A^\delta_\alpha B^\alpha_\beta C^\beta_\gamma D^\gamma_\delta$$



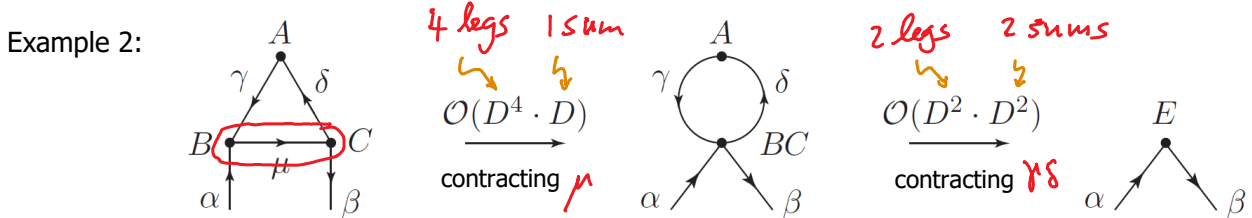
Cost of computing contractions

Result of contraction does not depend on order in which indices are summed, but numerical cost does !

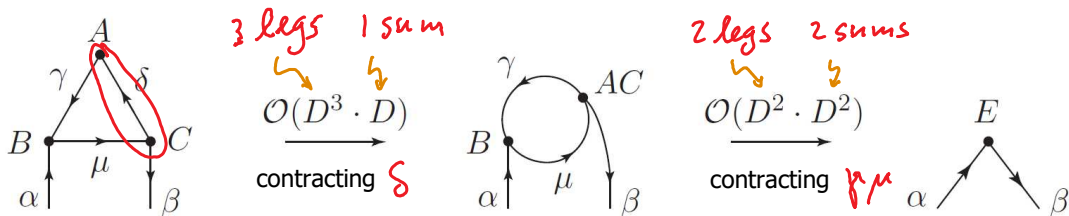
Example 1: cost of matrix multiplication is $O(D^3)$: 

For every fixed α and γ ($D_\alpha \times D_\gamma$ combinations), sum over D_β values of β

Cost = $D_\alpha \cdot D_\gamma \cdot D_\beta$ (simplifies to D^3 if all bond dimensions are = D)



$$A^\delta_\gamma (B^{\gamma\alpha}_\mu C^\mu_{\beta\delta}) = A^\delta_\gamma (BC)^{\gamma\alpha}_{\beta\delta} = E^\alpha_\beta$$



$$B^{\gamma\alpha}_\mu \underbrace{(A^\delta_\gamma C^\mu_{\beta\delta})}_{\text{independent of } \alpha} = B^{\gamma\alpha}_\mu (AC)^\mu_{\gamma\beta} = E^\alpha_\beta$$

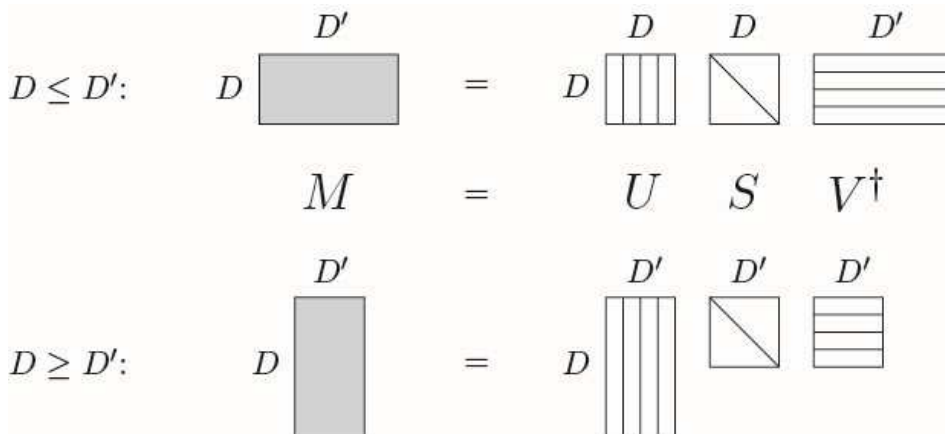
First contraction scheme has total cost $O(D^5)$, second has $O(D^4)$!!

Finding optimal contraction order is difficult problem! In practice: rely on experience, trial and error...

In first two-thirds of course, we will focus on 1D tensor networks. 2D will come after that.

Any matrix M of dimension $D \times D'$ can be written as

$$M = USV^T \quad (1)$$



Properties of S

- square matrix, of dimension $D_{min} \times D_{min}$, with $D_{min} = \min(D, D')$
- diagonal, with non-negative diagonal elements, called 'singular values' $S_{\alpha} \equiv S_{\alpha\alpha}$
- 'Schmidt rank' r : number of non-zero singular values
- arrange in descending order: $S_1 \geq S_2 \geq \dots \geq S_r > 0$

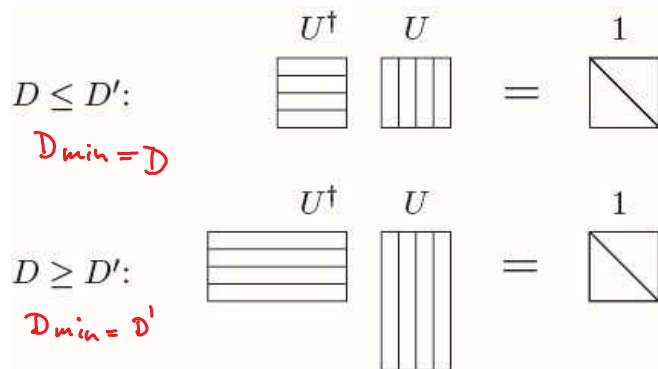
$$\Rightarrow S = \text{diag}(s_1, s_2, \dots, s_r, \underbrace{0, \dots, 0}_{D_{min}-r \text{ zeros}}) \quad (2)$$

Properties of U:

- matrix of dimension $D \times D_{min}$
- columns are orthonormal:

$$U^T U = \mathbb{1} \quad (3)$$

$$U U^T \neq \mathbb{1}$$

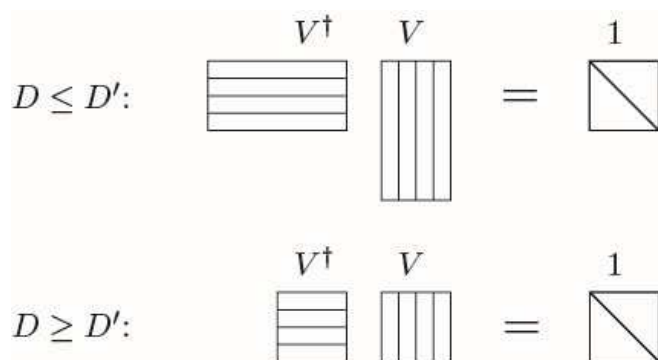


Properties of V^T:

- matrix of dimension $D_{min} \times D'$
- rows are orthonormal:

$$V^T V = \mathbb{1} \quad (4)$$

$$V V^T \neq \mathbb{1}$$



(1), (3), (4) imply:

$$MM^T \stackrel{(1)}{=} USV^T V S U^T \stackrel{(4)}{=} US^2 U^T \stackrel{(3)}{\Rightarrow} U^T M M^T U = S^2 \quad (5)$$

$$M^T M \stackrel{(1)}{=} V S U^T U S V^T \stackrel{(3)}{=} V S^2 V^T \stackrel{(4)}{\Rightarrow} V^T M^T M V = S^2 \quad (6)$$

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

Truncation

SVD yields optimal approximation of rank τ matrix M by a rank $\tau' (< \tau)$ matrix M' :

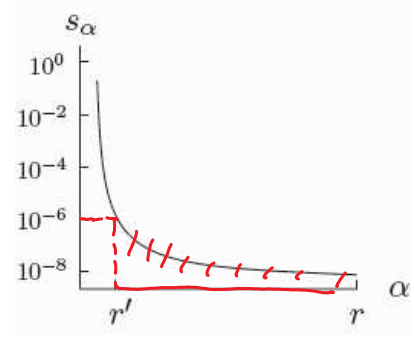
(optimal w.r.t. the Frobenius norm: $\|M\|_F^2 \equiv \sum_{\alpha\beta} |M_{\alpha\beta}|^2$)

Suppose $M = USV^T$ (7)

with $S = \text{diag}(s_1, s_2, \dots, s_r, \underbrace{0, \dots, 0}_{D_{\min} - \tau \text{ zeros}})$ (8)

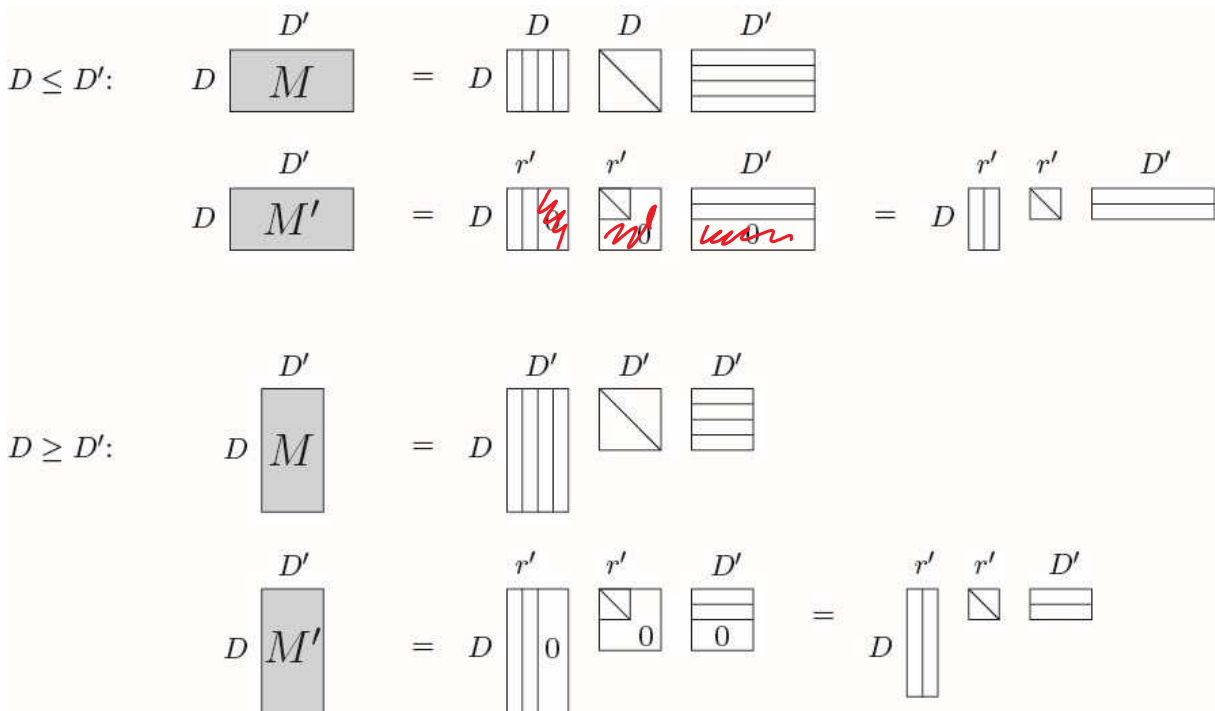
Truncate: $M' = US'V^T$ (9)

with $S' = \text{diag}(s_1, s_2, \dots, s_{r'}, \underbrace{\dots, 0, \dots, 0}_{D_{\min} - \tau' \text{ zeros}})$ (10)



Retain only τ' largest singular values!

Visualization, with $\tau = D_{\min}$:



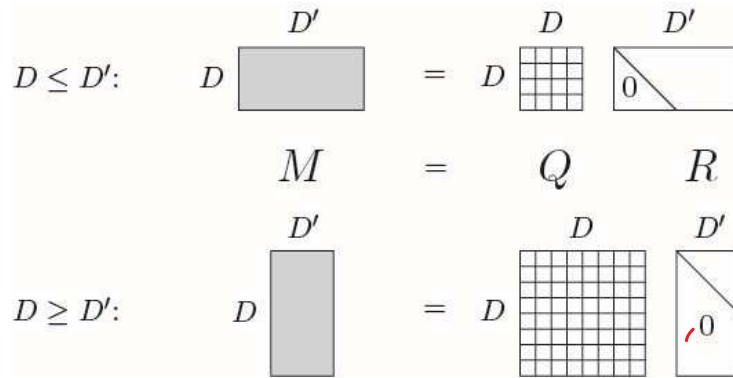
QR-decomposition

If singular values are not needed,

a $D \times D'$ matrix M

has the 'full QR decomposition'

$$M = QR \quad (11)$$



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

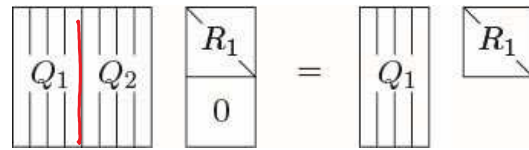
and R a $D \times D'$ upper triangular matrix,

$$QQ^T = Q^TQ = \mathbf{1}$$

$$R_{\alpha\beta} = 0 \text{ if } \alpha > \beta$$

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

$$M = (Q_1, Q_2) \cdot \begin{pmatrix} R_1 \\ 0 \end{pmatrix} = Q_1 \cdot R \quad (12)$$



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

$$Q_i^T Q_i = \mathbf{1} \text{ but } Q_i Q_i^T \neq \mathbf{1} \quad (13)$$

and R_1 upper triangular.

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