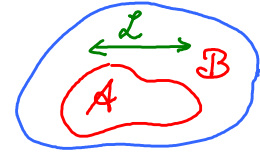


1. Entanglement Entropy and Area Laws (introductory comments)

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 .



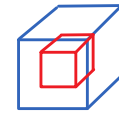
To obtain reduced density matrix of A (or B), trace out B (or A):

'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 : $S_{A/B} = -\text{Tr}_A \hat{\rho}_A \log_2 \hat{\rho}_A = -\sum_{\alpha} w_{\alpha} \log_2 w_{\alpha}$ (2)
eigenvalues of $\hat{\rho}_A$

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

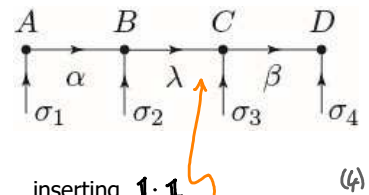
- $S \equiv S_{A/B} \sim$ (area of boundary of A) $\equiv \partial A$ (3)
- $\sim L^2$ in 3D for gapped system (3a)
- $\sim L$ in 2D for gapped system (3b)
- $\sim \text{const.}$ in 1D for gapped system (3c)
- $\sim \text{const.} + \ln N$ in 1D for gapless system (3d)



Now consider an MPS of maximal bond dimension D :

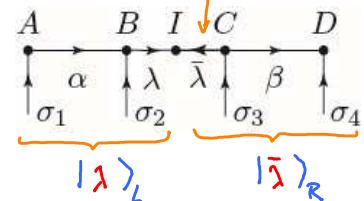
$$|\psi\rangle = |\sigma_4\rangle \otimes |\sigma_3\rangle \otimes |\sigma_2\rangle \otimes |\sigma_1\rangle A_{\alpha}^{\sigma_1} B^{\alpha\sigma_2}_{\lambda} \mathbb{1}^{\lambda\bar{\lambda}} \mathbb{1}^{\bar{\lambda}\lambda'} C^{\lambda'\sigma_3}_{\beta} D^{\beta\sigma_4}$$

unit tensor $\equiv \delta^{\lambda\bar{\lambda}}$



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

inserting $\mathbb{1} \cdot \mathbb{1}$ effectively inverts arrow (4)



$$|\psi\rangle = \mathbb{1}^{\lambda\bar{\lambda}} \underbrace{|\sigma_4\rangle \otimes |\sigma_3\rangle C^{\sigma_3}_{\bar{\lambda}\beta} D^{\beta\sigma_4}}_{|\bar{\lambda}\rangle_R} \otimes \underbrace{|\sigma_2\rangle \otimes |\sigma_1\rangle A^{\sigma_1}_{\alpha} B^{\alpha\sigma_2}_{\lambda}}_{|\lambda\rangle_L}$$

$$= \sum_{\lambda, \bar{\lambda}} \mathbb{1}^{\lambda\bar{\lambda}} |\bar{\lambda}\rangle_R \otimes |\lambda\rangle_L$$

= entangled superposition of two state spaces, each having dimension of at most D (5)

$$= \sum_{\lambda=1}^D |\lambda\rangle \otimes |\lambda\rangle$$

(After the sum over $\bar{\lambda}$ has been performed explicitly using the Kronecker delta, the result contains non-covariantly paired indices.) (3)

suppress \otimes henceforth

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

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

with matrix elements

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

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

Entanglement entropy:

$S^A \stackrel{(2)}{=} - \sum_{\alpha=1}^D \omega_{\alpha} \log_2 \omega_{\alpha}$

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)

$\Rightarrow 2^{S^A} \leq D$ (14)

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

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

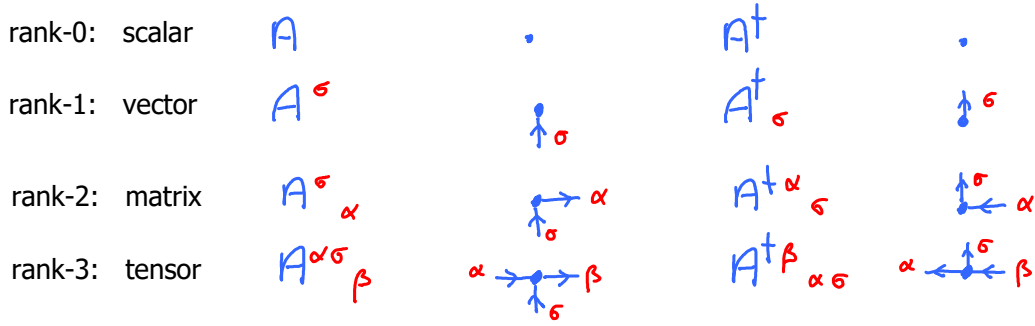
2D gapped: $\sim 2^L$ (15c)

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

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

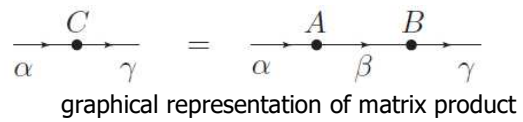
'tensor' = multi-dimensional array of numbers

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



Index contraction: summation over repeated index

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



D_β = 'bond dimension' of index β

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

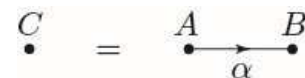
'open index' = non-contracted index (here α, γ)

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

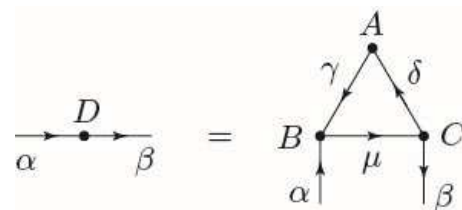
Examples:

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

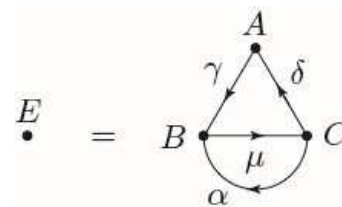
scalar vector \cdot dual vector



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

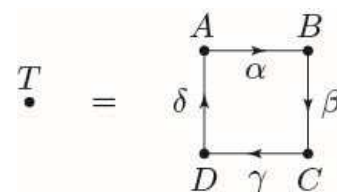


$$E = D^\alpha_\alpha = A^\delta_\gamma B^{\gamma\alpha}_\mu C^{\mu\delta}_\alpha$$



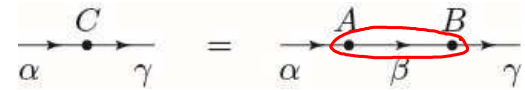
Trace of matrix product:

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



Cost of computing contractions

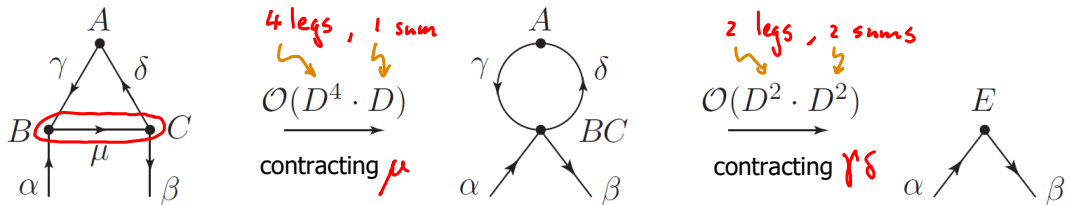
Result of contraction does not depend on order in which indices are summed, but numerical cost does !

Example 1: cost of matrix multiplication is $\mathcal{O}(D^3)$: 

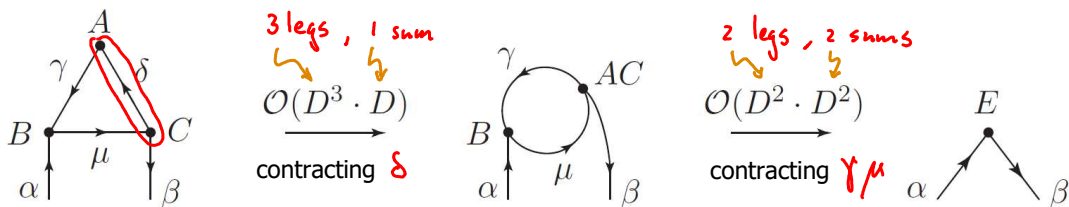
For every fixed α and γ ($D_\alpha \times D_\gamma$ combinations), sum over D_β values of β

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

Example 2:



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



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

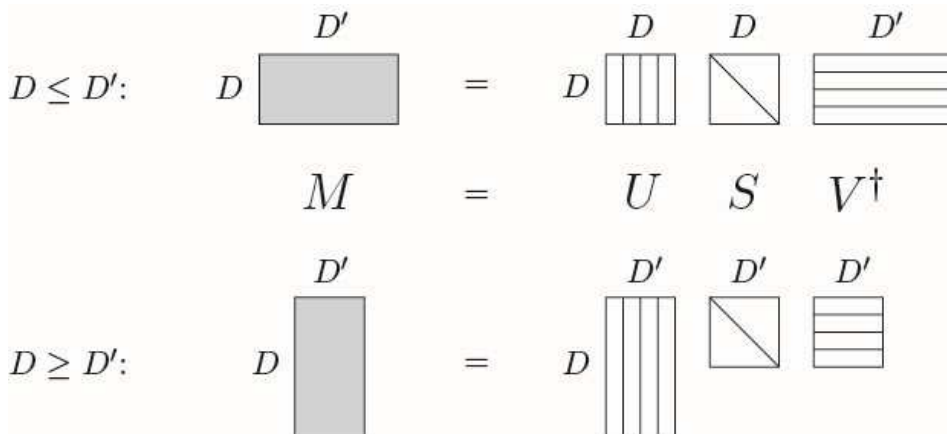
First contraction scheme has total cost $\mathcal{O}(D^5)$, second has $\mathcal{O}(D^4)$!!

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

$$M = U S V^\dagger \quad (1)$$



Properties of S

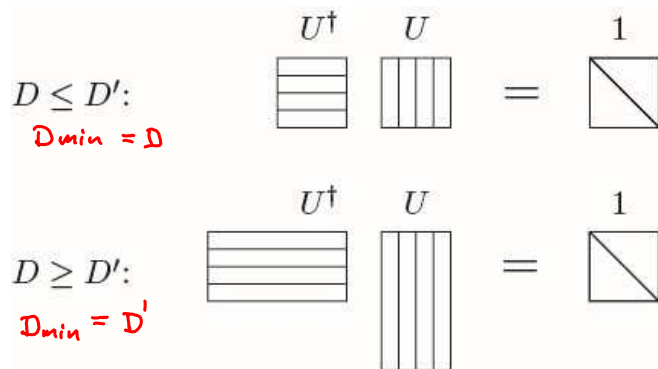
- square matrix, of dimension $D_{min} \times D_{min}$, with $D_{min} = \min(D, D')$
 - diagonal, with non-negative diagonal elements, called 'singular values' $S_\alpha \equiv S_{\alpha\alpha}$
 - 'Schmidt rank' r : number of non-zero singular values
 - arrange in descending order: $S_1 \geq S_2 \geq \dots \geq S_r > 0$
- $\Rightarrow S = \text{diag}(s_1, s_2, \dots, s_r, \underbrace{0, \dots, 0}_{D_{min} - r} \text{ zeros})$ (2)

Properties of U:

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

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

but $U U^\dagger \neq \mathbb{1}$
(not unitary)

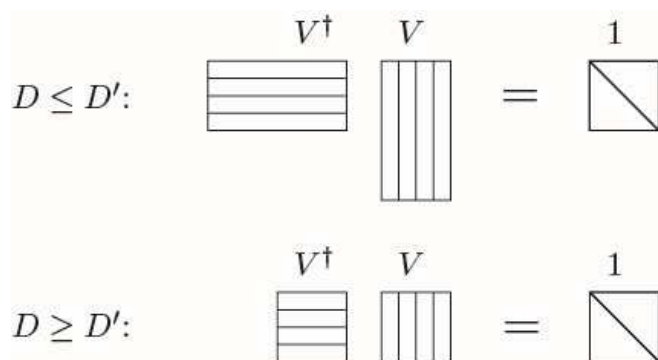


Properties of V†:

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

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

but $V V^\dagger \neq \mathbb{1}$
(not unitary)



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

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

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

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' :

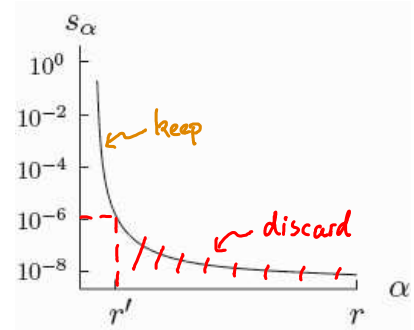
(optimal w.r.t. the Frobenius norm: $\|M\|_F^2 \equiv \sum_{\alpha\beta} |M_{\alpha\beta}|^2$)

Suppose $M = USV^T$ (7)

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

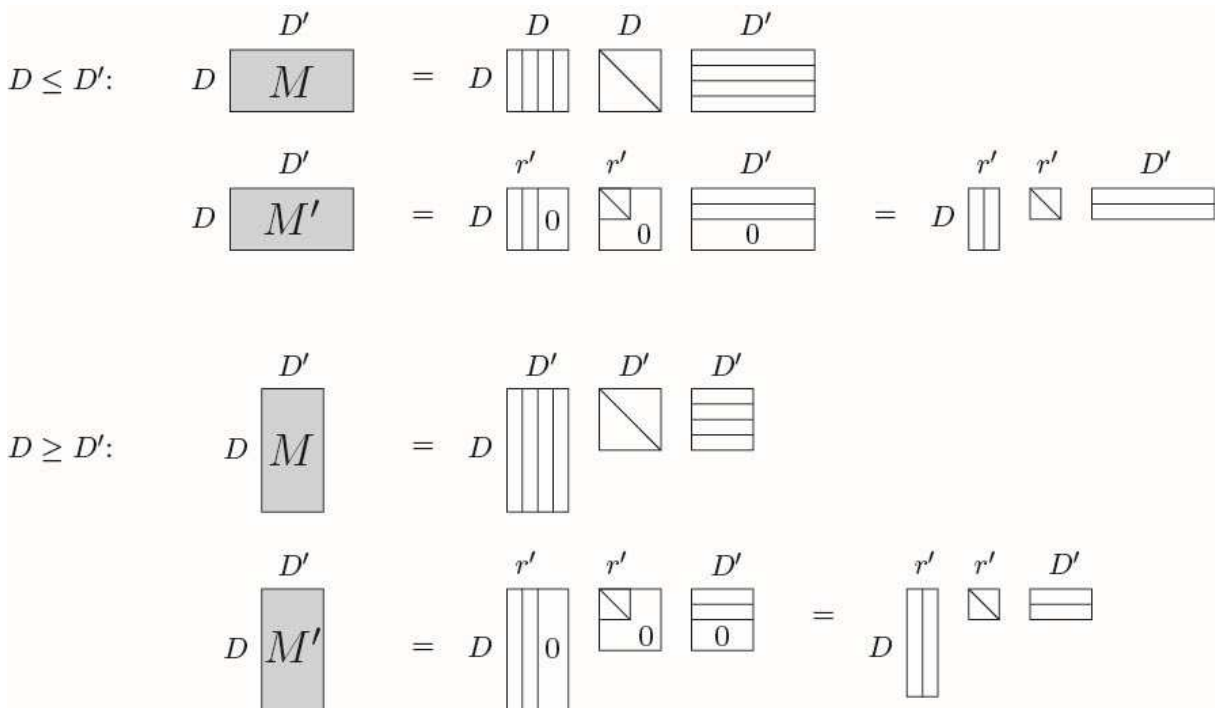
Truncate: $M' = US'V^T$ (9)

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



Retain only τ' largest singular values!

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



QR-decomposition

If singular values are not needed,

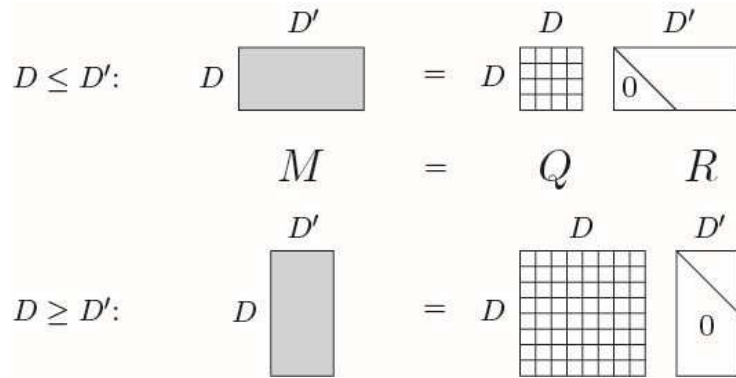
a $D \times D'$ matrix M

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,

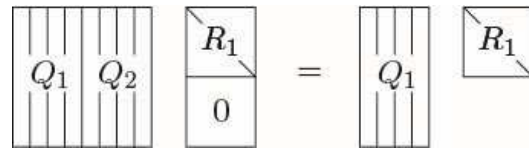


$$QQ^T = Q^TQ = \mathbf{1}$$

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

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

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



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

$$Q_1^T Q_1 = \mathbf{1} \text{ but } Q_1 Q_1^T \neq \mathbf{1} \quad (13)$$

and R_1 upper triangular.

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