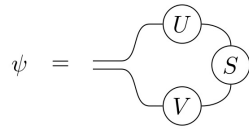


Exercise 8.1 (Schmidt decomposition and entanglement entropy)

Let $\psi \in \mathbb{C}^{m \times n}$ be a complex vector. We may interpret ψ as $m \times n$ matrix and compute its SVD, for which we use the convention $\psi = USV^T$ here, with isometries $U \in \mathbb{C}^{m \times k}$, $V \in \mathbb{C}^{n \times k}$ (such that $U^\dagger U = I$ and $V^\dagger V = I$), $k = \min(m, n)$ and $S = \text{diag}(\sigma_1, \dots, \sigma_k)$. (The V matrix appears without complex conjugation in the SVD.) As graphical diagram:



(a) Show that

$$\|\psi\|^2 = \sum_{j=1}^k \sigma_j^2.$$

Hint: Revisit the definition and properties of the Frobenius norm, or use the diagrammatic representation.

g) $\|\psi\|^2 \stackrel{①}{=} \|\psi\|_F^2 \stackrel{②}{=} \sqrt{\sum_j \delta_j^2(\psi)}^2 = \sum_j \sigma_j^2$ *Vorlesung* \rightarrow

- Frobenius norm:

① $\|A\|_F = \sqrt{\sum_{i,j} |a_{ij}|^2} = \|\text{vec}(A)\|$

since $\sum_{i,j} |a_{ij}|^2 = \text{tr}[A^\dagger A] = \sum_j \sigma_j^2(A)$

② $\|A\|_F = \sqrt{\sum_j \sigma_j^2(A)}$

(b) The partial trace has been introduced in Exercise 5.1. Here the two subsystems have dimension m and n , respectively. Verify that

$$\text{tr}_2[\psi \circ \psi^*] = US^2U^\dagger \quad \text{and}$$

$$\text{tr}_1[\psi \circ \psi^*] = VS^2V^\dagger.$$

$\text{tr}_2[\psi \circ \psi^*] =$

$= U \cdot S \cdot V^T \cdot V^* \cdot S^\dagger \cdot U^\dagger = U S (V V^\dagger)^T S^\dagger U^\dagger = U S S^\dagger U^\dagger = U S^2 U^\dagger$

$\text{tr}_1[\psi \circ \psi^*] =$

$= V S^\dagger U^\dagger U^* S^* V^T = V S S V^\dagger = V S^2 V^\dagger$

In part (b) we have thus found the spectral decompositions of the “reduced density matrices” defined as $\rho_1 = \text{tr}_2[\psi \circ \psi^*]$ and $\rho_2 = \text{tr}_1[\psi \circ \psi^*]$ (potentially omitting zero eigenvalues). One observes that ρ_1 and ρ_2 have the same (non-zero) eigenvalues $(\sigma_j^2)_{j=1, \dots, k}$. In the following, we assume that $\|\psi\| = 1$, such that $\sum_{j=1}^k \sigma_j^2 = 1$ according to (a).

In general, a density matrix ρ is a Hermitian, positive semidefinite matrix with normalization $\text{tr}[\rho] = 1$. The *von Neumann entropy* of ρ is defined as

$$S(\rho) = -\text{tr}[\rho \log(\rho)],$$

with the logarithm interpreted as matrix function, and the convention $0 \log(0) = \lim_{x \rightarrow 0} x \log(x) = 0$.

In the present setting, the *entanglement entropy* between the two subsystems is defined as

$$S_{\text{ent}} = S(\rho_1) = S(\rho_2) = -\sum_{j=1}^k \sigma_j^2 \log(\sigma_j^2).$$

(You should convince yourself that $S(\rho_1)$ and $S(\rho_2)$ are indeed equal to the sum on the right.) Intuitively, the entanglement entropy measures how strongly the subsystems are intertwined.

- (c) Which singular values $(\sigma_j)_{j=1, \dots, k}$ minimize and maximize the entanglement entropy, respectively, under the normalization condition $\sum_{j=1}^k \sigma_j^2 = 1$? (k should be regarded as given and fixed.)

Hint: The smallest possible entanglement entropy is zero. Regarding maximization, first consider the case $k = 2$.

minimal entropy: $\sigma = (1, 0, \dots, 0) \Rightarrow 1 \log(1) + (k-1) \cdot 0 \cdot \log(0) = \underline{0}$
 \uparrow
beliebiger Index

maximal entropy: distribution as even as possible:

$$\sigma = \left(\frac{1}{\sqrt{k}}, \frac{1}{\sqrt{k}}, \dots\right) \Rightarrow S = -k \cdot \frac{1}{k} \cdot \log\left(\frac{1}{k}\right) = \underline{\underline{\log(k)}}$$

8.1d

— we have

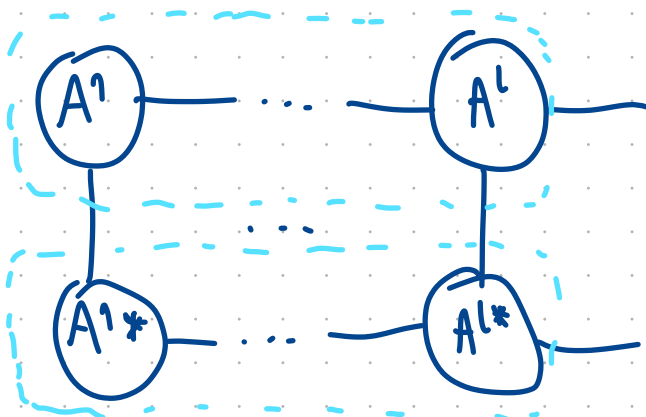
$\Psi_{\leq l}$



Then



=

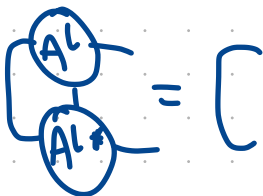


=

[

A^l are isometries

\Rightarrow can apply

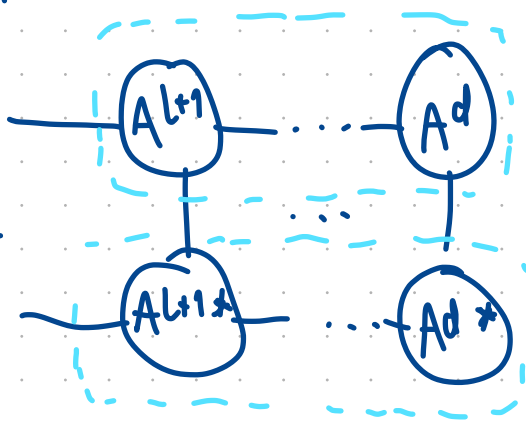


from lecture

— same for $\Psi_{\geq l+1}$:



=



=

[

exercise8.2_template

June 22, 2022

1 Canonical MPS forms

```
[1]: import numpy as np
import matplotlib.pyplot as plt
```

1.1 Functions for conversion to canonical forms

```
[2]: def mps_orthonormalize_left(Alist, stop=-1):
    """
    Left-orthonormalize a MPS using QR decompositions.
    The list of tensors in `Alist` are updated in-place.

    Returns the overall norm of the original MPS. (The updated MPS has norm 1.)
    """
    dummy = np.array([[[1]]])
    d = len(Alist)
    if (stop > 0):
        d = stop

    for l in range(d):
        n, dlm, dl = Alist[l].shape
        A = Alist[l].reshape((n * dlm, dl))
        Q, R = np.linalg.qr(A)
        dl = Q.shape[1]
        Alist[l] = Q.reshape((n, dlm, dl))
        if (l < len(Alist) - 1):
            Alist[l + 1] = np.moveaxis(np.tensordot(R, Alist[l + 1], ([1],
↪ [1])), 0, 1)
        else:
            dummy = np.moveaxis(np.tensordot(R, dummy, ([1], [1])), 0, 1)

    dummy = dummy[0, 0, 0]
    if dummy < 0:
        dummy *= -1
        Alist[d - 1] = -1 * Alist[d - 1]

    return dummy
```

```
[3]: def mps_orthonormalize_right(Alist, stop=-1):
    """
    Right-orthonormalize a MPS using QR decompositions.
    The list of tensors in `Alist` are updated in-place.

    Returns the overall norm of the original MPS. (The updated MPS has norm 1.)
    """
    MirList = []

    for l in range(len(Alist) - 1, -1, -1):
        MirList.append(np.moveaxis(Alist[l], 1, 2))

    nrm = mps_orthonormalize_left(MirList, stop)

    for l in range(len(Alist)):
        Alist[len(Alist) - 1 - l] = np.moveaxis(MirList[l], 1, 2)

    return nrm
```

```
[4]: def mps_orthonormalize_center(Alist, j):
    """
    Convert a MPS to site-canonical form with center at site `j`, such that
    all tensors to the left are left-orthonormal, and
    all tensors to the right are right-orthonormal.
    The list of tensors in `Alist` are updated in-place.
    """
    mps_orthonormalize_right(Alist, stop=len(Alist) - j - 1)
    mps_orthonormalize_left(Alist, stop=j)
```

```
[5]: def mps_orthonormalize_bond(Alist, j):
    """
    Convert a MPS to bond-canonical form, with a list of "singular values"
    between the `j`-th and `j+1`-th tensor.
    The list of tensors in `Alist` are updated in-place.

    Returns the singular value list.
    """
    mps_orthonormalize_center(Alist, j)
    n, dlm, dl = Alist[j].shape
    A = Alist[j].reshape((n * dlm, dl))
    Q, R = np.linalg.qr(A)
    dl = Q.shape[1]
    Alist[j] = Q.reshape((n, dlm, dl))

    u, s, vh = np.linalg.svd(R)
    Alist[j] = np.tensordot(Alist[j], u, ([2], [0]))
    Alist[j+1] = np.tensordot(vh, Alist[j+1], ([1], [1])), 0, 1)
```

```
return s
```

1.2 Utility functions

```
[6]: def is_left_orthonormal(A):  
    """  
    Test whether a MPS tensor `A` is left-orthonormal.  
    """  
    s = A.shape  
    assert len(s) == 3  
    A = np.reshape(A, (s[0] * s[1], s[2]))  
    return np.allclose(A.conj().T @ A, np.identity(s[2]))
```

```
[7]: def is_right_orthonormal(A):  
    """  
    Test whether a MPS tensor `A` is right-orthonormal.  
    """  
    # call `is_left_orthonormal` with flipped left and right virtual bond  
    ↪ dimensions  
    return is_left_orthonormal(np.transpose(A, (0, 2, 1)))
```

```
[8]: def mps_to_full_tensor(Alist):  
    """  
    Construct the full tensor corresponding to the MPS tensors `Alist`.  
  
    The  $i$ -th MPS tensor  $Alist[i]$  is expected to have dimensions  $(n[i], D[i],$  ↪  
    ↪  $D[i+1])$ ,  
    with `n` the list of logical dimensions and `D` the list of virtual bond  
    ↪ dimensions.  
  
    Note: Should only be used for debugging and testing.  
    """  
    # consistency check: dummy singleton dimension  
    assert Alist[0].ndim == 3 and Alist[0].shape[1] == 1  
    # formally remove dummy singleton dimension  
    T = np.reshape(Alist[0], (Alist[0].shape[0], Alist[0].shape[2]))  
    # contract virtual bonds  
    for i in range(1, len(Alist)):  
        T = np.tensordot(T, Alist[i], axes=(-1, 1))  
    # consistency check: trailing dummy singleton dimension  
    assert T.shape[-1] == 1  
    # formally remove trailing singleton dimension  
    T = np.reshape(T, T.shape[:-1])  
    return T
```

```
[9]: def mps_bond_to_full_tensor(Alist, S, j):
    """
    Construct the full tensor corresponding to the bond-canonical MPS
    with tensors `Alist` and "bond" singular values `S` between
    the `j`-th and `j+1`-th tensor.
    """
    # absorb bond singular values into j-th tensor
    Blist = [np.tensordot(Alist[i], np.diag(S), (2, 1)) if i == j else Alist[i]
    ↪for i in range(len(Alist))]
    return mps_to_full_tensor(Blist)
```

```
[10]: def partial_trace(rho, dimA, dimB):
    """
    Compute the partial traces of a density matrix `rho` of a composite quantum
    ↪system AB.

    Args:
        rho: density matrix of dimension dimA*dimB x dimA*dimB
        dimA: dimension of subsystem A
        dimB: dimension of subsystem B
    Returns:
        tuple: reduced density matrices for subsystems A and B
    """
    # explicit subsystem dimensions
    rho = np.reshape(rho, (dimA, dimB, dimA, dimB))
    # trace out subsystem B
    rhoA = np.trace(rho, axis1=1, axis2=3)
    # trace out subsystem A
    rhoB = np.trace(rho, axis1=0, axis2=2)
    return rhoA, rhoB
```

```
[11]: def crandn(size):
    """
    Draw random samples from the standard complex normal (Gaussian)
    ↪distribution.
    """
    # 1/sqrt(2) is a normalization factor
    return (np.random.normal(size=size) + 1j * np.random.normal(size=size)) /
    ↪np.sqrt(2)
```

```
[12]: def xlogx(x):
    """
    Compute `x * log(x)` (pointwise), such that the result is zero for `x = 0`.
    """
    y = np.zeros_like(x)
    idx = x > 0
    y[idx] = x[idx] * np.log(x[idx])
```

```
return y
```

1.3 Examples and tests

```
[13]: # logical and virtual bond dimensions (rather arbitrarily chosen)
n = [2, 5, 3, 4, 6, 3]
D = [1, 3, 4, 7, 6, 5, 1]
```

```
[14]: # random MPS tensors (the scaling factor keeps the norm of the full tensor in a
      ↪ reasonable range)
np.random.seed(142)
Aref = [0.3 * crandn((n[i], D[i], D[i + 1])) for i in range(len(n))]

# the tensors are randomly chosen, and in particular not of any normal form
print([is_left_orthonormal(A) for A in Aref])
print([is_right_orthonormal(A) for A in Aref])

# construct the full (dense) tensor which this MPS represents, as reference
      ↪ (should only be constructed for testing and debugging)
Tref = mps_to_full_tensor(Aref)
# its shape must be equal to `n` from above:
print("Tref.shape:", Tref.shape)
```

```
[False, False, False, False, False, False]
[False, False, False, False, False, False]
Tref.shape: (2, 5, 3, 4, 6, 3)
```

1.3.1 Left-orthonormalization

```
[15]: # first make a copy of the input tensors
AL = [A.copy() for A in Aref]

# function returns norm of input MPS
nrmL = mps_orthonormalize_left(AL)
```

```
[16]: # these should all be True
[is_left_orthonormal(A) for A in AL]
```

```
[16]: [True, True, True, True, True, True]
```

```
[17]: nrmL
```

```
[17]: (1.2965535991355326-0j)
```

```
[18]: # compare norm with reference
abs(nrmL - np.linalg.norm(np.reshape(Tref, -1))) / abs(nrmL)
```


[18]: 1.7125755932734126e-16

```
[19]: # compare full tensor with reference: difference should be zero (up to
      ↪ numerical rounding errors)
      np.linalg.norm(nrmL * mps_to_full_tensor(AL) - Tref)
```

[19]: 1.1619396826252498e-15

1.3.2 Right-orthonormalization

```
[20]: # first make a copy of the input tensors
      AR = [A.copy() for A in Aref]

      # function returns norm of input MPS
      nrmR = mps_orthonormalize_right(AR)
```

```
[21]: # these should all be True
      [is_right_orthonormal(A) for A in AR]
```

[21]: [True, True, True, True, True, True]

```
[22]: nrmR
```

[22]: (1.2965535991355326-0j)

```
[23]: # compare norm with reference
      abs(nrmR - np.linalg.norm(np.reshape(Tref, -1))) / abs(nrmR)
```

[23]: 1.7125755932734126e-16

```
[24]: # compare full tensor with reference: difference should be zero (up to
      ↪ numerical rounding errors)
      np.linalg.norm(nrmR * mps_to_full_tensor(AR) - Tref)
```

[24]: 9.091941358304111e-16

1.3.3 Site-canonical form

```
[25]: # again make a copy first
      AC = [A.copy() for A in Aref]

      # tensors are updated in-place, and overall norm is preserved (function has no
      ↪ formal return value)
      jcenter = 2
      mps_orthonormalize_center(AC, jcenter)
```

```
[26]: # these should all be True
      [is_left_orthonormal(A) for A in AC[:jcenter]]
```

```
[26]: [True, True]
```

```
[27]: # these should all be True
      [is_right_orthonormal(A) for A in AC[jcenter + 1:]]
```

```
[27]: [True, True, True]
```

```
[28]: # "center" tensor is not orthonormal in general
      is_left_orthonormal(AC[jcenter]) or is_right_orthonormal(AC[jcenter])
```

```
[28]: False
```

```
[29]: # compare full tensor with reference: difference should be zero (up to
      ↪ numerical rounding errors)
      np.linalg.norm(mps_to_full_tensor(AC) - Tref)
```

```
[29]: 1.0487378834340819e-15
```

1.3.4 Bond-canonical form

```
[30]: # again make a copy first
      AB = [A.copy() for A in Aref]

      jbond = 3
      S = mps_orthonormalize_bond(AB, jbond)
```

```
[31]: # list of singular values for "cut" at `jbond`
      S
```

```
[31]: array([0.85731111, 0.65318151, 0.47655434, 0.39473114, 0.27652958,
          0.24502551])
```

```
[32]: # these should all be True
      [is_left_orthonormal(AB[j]) if j <= jbond else is_right_orthonormal(AB[j]) for
      ↪ j in range(len(AB))]
```

```
[32]: [True, True, True, True, True, True]
```

```
[33]: # compare full tensor with reference: difference should be zero (up to
      ↪ numerical rounding errors)
      np.linalg.norm(mps_bond_to_full_tensor(AB, S, jbond) - Tref)
```

```
[33]: 1.7067211880195904e-15
```

1.3.5 Bond-singular values and entanglement entropy

```
[34]: # compute (reduced) density matrices, as reference
      ref = np.outer(Tref, Tref.conj())
      A, B = partial_trace(ref, np.prod(n[:jbond + 1]), np.prod(n[jbond + 1:]))
      print(" A.shape:", A.shape)
      print(" B.shape:", B.shape)
```

```
A.shape: (120, 120)
B.shape: (18, 18)
```

```
[35]: # must be Hermitian
      np.linalg.norm(A - A.conj().T)
```

```
[35]: 0.0
```

```
[36]: # must be Hermitian
      np.linalg.norm(B - B.conj().T)
```

```
[36]: 0.0
```

```
[37]: A = np.linalg.eigvalsh(A)
      B = np.linalg.eigvalsh(B)
```

```
[38]: # most of them are actually zero
      A
```

```
[38]: array([-1.04158612e-16, -5.04120978e-17, -4.50643064e-17, -3.09628817e-17,
        -2.92487789e-17, -2.39908171e-17, -2.17945332e-17, -1.98333707e-17,
        -1.89664610e-17, -1.81748522e-17, -1.74202110e-17, -1.62433203e-17,
        -1.57288746e-17, -1.43154575e-17, -1.31744569e-17, -1.26977622e-17,
        -1.22028703e-17, -1.15573641e-17, -1.02748257e-17, -9.90329461e-18,
        -9.32509903e-18, -9.11640131e-18, -8.80149185e-18, -8.23987295e-18,
        -7.97671527e-18, -7.68367130e-18, -6.95259961e-18, -6.71073554e-18,
        -5.75320734e-18, -5.72178755e-18, -5.40778056e-18, -5.29059690e-18,
        -5.02807036e-18, -4.98842715e-18, -4.42073308e-18, -4.03270891e-18,
        -3.93415140e-18, -3.55608057e-18, -3.31606560e-18, -3.18667250e-18,
        -2.89392410e-18, -2.68396704e-18, -2.42062683e-18, -2.39460665e-18,
        -2.06096854e-18, -1.85741554e-18, -1.56622145e-18, -1.37198632e-18,
        -1.12395548e-18, -1.03684293e-18, -8.92166230e-19, -7.53258851e-19,
        -5.07123027e-19, -2.83237633e-19, -8.94118762e-20, 3.69924403e-21,
         4.17532460e-20, 1.20141516e-19, 2.61110534e-19, 3.85164442e-19,
         5.68331019e-19, 8.42177785e-19, 9.82611577e-19, 1.06496995e-18,
         1.20556263e-18, 1.33102835e-18, 1.53859718e-18, 1.63588470e-18,
         1.87965451e-18, 2.09521344e-18, 2.26005779e-18, 2.32445198e-18,
         2.51498965e-18, 2.90614325e-18, 3.07378425e-18, 3.24704011e-18,
         3.54241293e-18, 3.84657522e-18, 4.22021222e-18, 4.46631477e-18,
         4.63791846e-18, 5.12476071e-18, 5.27075754e-18, 5.67435143e-18,
```

```

5.80687970e-18, 6.07796628e-18, 6.41923071e-18, 7.09885664e-18,
7.31865144e-18, 8.01886322e-18, 8.41007922e-18, 8.81528485e-18,
9.37137755e-18, 9.85957449e-18, 1.01493903e-17, 1.06423592e-17,
1.17630356e-17, 1.19311664e-17, 1.27264057e-17, 1.33188034e-17,
1.40625300e-17, 1.51276125e-17, 1.54795781e-17, 1.73981649e-17,
1.83436600e-17, 2.02974773e-17, 2.20547510e-17, 2.32568787e-17,
2.52686264e-17, 2.83287153e-17, 3.62885082e-17, 5.32190097e-17,
6.48773579e-17, 9.00037809e-17, 6.00375012e-02, 7.64686066e-02,
1.55812673e-01, 2.27104043e-01, 4.26646080e-01, 7.34982332e-01])

```

```

[39]: # filter out zero eigenvalues
A = A[np.logical_not(np.isclose(A, 0, atol=1e-13))]
B = B[np.logical_not(np.isclose(B, 0, atol=1e-13))]

# sort in descending order
A = np.sort(A)[::-1]
B = np.sort(B)[::-1]

```

```
[40]: A
```

```
[40]: array([0.73498233, 0.42664608, 0.22710404, 0.15581267, 0.07646861,
0.0600375 ])
```

```

[41]: # compare: should agree
np.linalg.norm(A - B)

```

```
[41]: 3.632164660233972e-16
```

```

[42]: # compare: should agree with bond-singular values from above
np.linalg.norm(A - S ** 2)

```

```
[42]: 7.132224383467466e-16
```

```

[43]: # normalize singular values
Snrm = S / np.linalg.norm(S)
Snrm

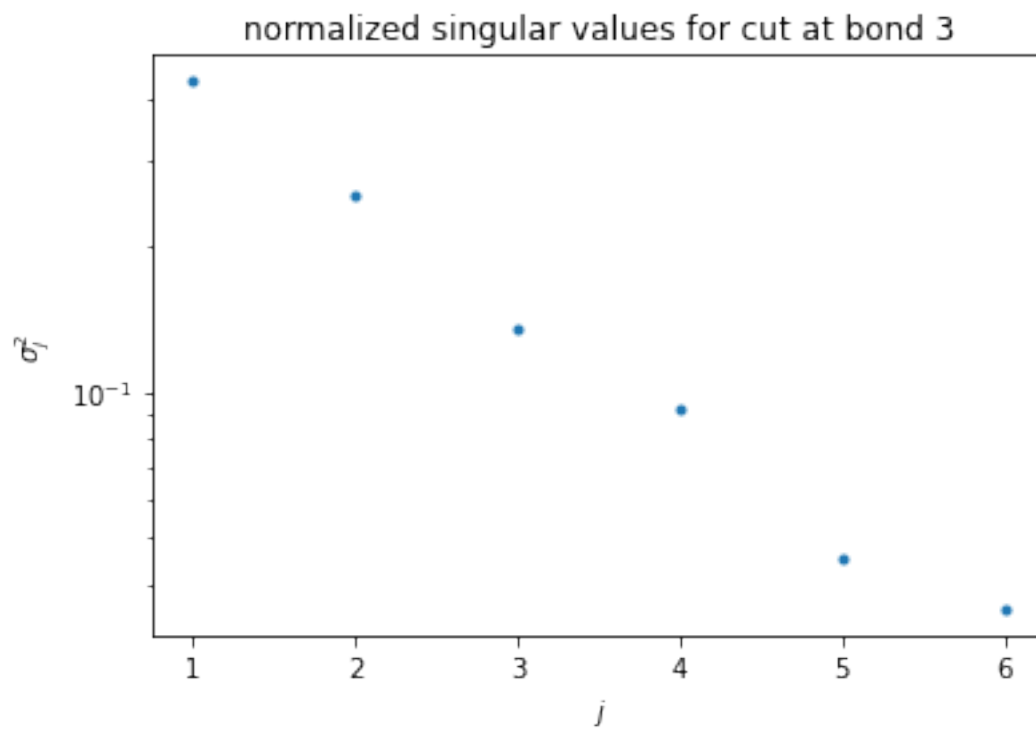
```

```
[43]: array([0.66122303, 0.50378288, 0.36755468, 0.30444645, 0.21328048,
0.18898217])
```

```

[44]: plt.semilogy(range(1, len(Snrm) + 1), Snrm ** 2, '.')
plt.ylabel("$\\sigma_j^2$")
plt.xlabel("$j$")
plt.title("normalized singular values for cut at bond {}".format(jbond))
plt.show()

```



```
[45]: # finally compute entanglement entropy  
np.sum(-xlogx(Snrm ** 2))
```

```
[45]: 1.460203986361991
```