# Color Network Document

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由于对本领域并不熟悉,本文档会夹杂中文。

## 第一章 Basic Topics

#### 1.0.1 NRG and DMRG

Here we will introduce numerical renormalization group and density matrix renormalization group using an example to solve an equation of a single particle.

We will consider solving such an equation in range  $x \in [-1, 1]$ .

$$\frac{\partial^2}{\partial x^2} f(x) = af(x),$$

$$f(-1) = f(1) = 0,$$
(1.1)

with

$$\frac{\partial^2}{\partial x^2} f(x) \approx \frac{f(x + \Delta x) + f(x - \Delta x) - 2f(x)}{\Delta x^2},\tag{1.2}$$

the discretized version is an eigen-problem

$$\frac{1}{\Delta x^2} \begin{pmatrix}
2 & -1 & 0 & 0 & \dots & 0 & 0 \\
-1 & 2 & -1 & 0 & \dots & 0 & 0 & 0 \\
0 & -1 & 2 & -1 & \dots & 0 & 0 & 0 \\
0 & 0 & -1 & 2 & \dots & 0 & 0 & 0 & 0 \\
\dots & \dots \\
0 & 0 & 0 & 0 & \dots & 2 & -1 & 0 & 0
\end{pmatrix} f = af, \tag{1.3}$$

It can be written as

$$\frac{1}{\Delta x^2} \begin{pmatrix} H_0 & L_0 & 0 & 0 & \dots & 0 & 0 \\ L_0 & H_0 & L_0 & 0 & \dots & 0 & 0 \\ 0 & L_0 & H_0 & L_0 & \dots & 0 & 0 \\ 0 & 0 & L_0 & H_0 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & \dots & H_0 & L_0 \\ 0 & 0 & 0 & 0 & \dots & L_0 & H_0 \end{pmatrix} f \approx \frac{1}{\Delta x^2} \begin{pmatrix} H_0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & H_0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & H_0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & H_0 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & \dots & H_0 & 0 \\ 0 & 0 & 0 & 0 & \dots & H_0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & H_0 \end{pmatrix} = af,$$

$$(1.4)$$

with

The first step is to solve eigen system of H, the two lowest eigen values and eigen vectors are

$$H_{0} \begin{pmatrix} \frac{1}{5+\sqrt{5}} & -\frac{1}{5-\sqrt{5}} \\ \frac{1}{2\sqrt{5}} & -\frac{1}{2\sqrt{5}} \\ \frac{1}{2\sqrt{5}} & \frac{1}{2\sqrt{5}} \\ \frac{1}{5+\sqrt{5}} & \frac{1}{5-\sqrt{5}} \end{pmatrix} = \begin{pmatrix} \frac{1}{5+\sqrt{5}} & -\frac{1}{5-\sqrt{5}} \\ \frac{3-\sqrt{5}}{2} \times \frac{1}{2\sqrt{5}} & \frac{5-\sqrt{5}}{2} \times \frac{1}{2\sqrt{5}} \\ \frac{1}{5+\sqrt{5}} & \frac{1}{5-\sqrt{5}} \end{pmatrix}$$
(1.6)

Then, truncate use

$$U = \begin{pmatrix} \frac{1}{5+\sqrt{5}} & -\frac{1}{5-\sqrt{5}} \\ \frac{1}{2\sqrt{5}} & -\frac{1}{2\sqrt{5}} \\ \frac{1}{2\sqrt{5}} & \frac{1}{2\sqrt{5}} \\ \frac{1}{5+\sqrt{5}} & \frac{1}{5-\sqrt{5}} \end{pmatrix}$$

$$H' = U^{T}H_{0}U = \begin{pmatrix} \frac{1}{2} - \frac{1}{\sqrt{5}} & 0 \\ 0 & \frac{1}{2} \end{pmatrix}, \quad L' = U^{T}L_{0}U = \begin{pmatrix} -\frac{1}{(5+\sqrt{5})^{2}} & -\frac{1}{20} \\ \frac{1}{20} & \frac{1}{(5-\sqrt{5})^{2}} \end{pmatrix}.$$

$$(1.7)$$

Now, we are dealing with a truncated problem

$$\frac{1}{\Delta x^{2}} \begin{pmatrix}
H_{1} & L_{1} & 0 & 0 & \dots & 0 & 0 \\
L_{1} & H_{1} & L_{1} & 0 & \dots & 0 & 0 \\
0 & L_{1} & H_{1} & L_{1} & \dots & 0 & 0 \\
0 & 0 & L_{1} & H_{1} & \dots & 0 & 0 \\
\dots & \dots & \dots & \dots & \dots & \dots \\
0 & 0 & 0 & 0 & \dots & H_{1} & L_{1} \\
0 & 0 & 0 & 0 & \dots & L_{1} & H_{1}
\end{pmatrix} f = af, \tag{1.8}$$

with

$$H_{1} = \begin{pmatrix} H' & L' \\ L' & H' \end{pmatrix} = \begin{pmatrix} \frac{1}{2} - \frac{1}{\sqrt{5}} & 0 & -\frac{1}{(\sqrt{5}+5)^{2}} & \frac{1}{20} \\ 0 & \frac{1}{2} & -\frac{1}{20} & \frac{1}{(5-\sqrt{5})^{2}} \\ -\frac{1}{(\sqrt{5}+5)^{2}} & -\frac{1}{20} & \frac{1}{2} - \frac{1}{\sqrt{5}} & 0 \\ \frac{1}{20} & \frac{1}{(5-\sqrt{5})^{2}} & 0 & \frac{1}{2} \end{pmatrix},$$
(1.9)
$$L_{1} = \begin{pmatrix} 0 & L' \\ 0 & 0 \end{pmatrix}$$

Again, we solve  $H_1f=af$ , the lowest two eigenvalues are 0.067 and 0.026. As a compare, the lowest two eigenvalues of a 16  $\times$  16 original matrix are 0.135 and 0.034.

## 第二章 Decompose Methods

### 2.1 Matrix Decompose

#### 2.1.1 Matrix SVD using Lanczos

The matrix SVD is to decompose

$$t_{i_1,i_2,\dots,i_m,j_1,j_2,\dots,j_n} = \sum_{k_l,k_r} V_{i_1,i_2,\dots,i_m,k_l} S_{k_l,k_r} U_{k_r,j_1,j_2,\dots,j_n},$$
(2.1)

where

$$\sum_{k_l} V_{I_1,I_2,\dots,I_m,k_l}^* V_{i_1,i_2,\dots,i_m,k_l} = \delta_{(i_m)=(I_m)},$$

$$\sum_{k_r} U_{J_1,J_2,\dots,J_n,k_r}^* U_{j_1,j_2,\dots,j_m,k_l} = \delta_{(J_n)=(j_n)},$$

$$S_{k_l \neq k_r} = 0,$$
(2.2)

One can imagine that,  $\{i_n\}$  is ONE combined index of a matrix. Then, it is the normal SVD. Usually, dim(k) is small.

#### 2.1.1.1 Lanczos bidiagonalization

Lanczos bidiagonalization is for such task:

For  $A = C^{m \times n}$ , find  $A \approx UBV^{\dagger}$  such that B is a bidiagonal matrix

$$B = \begin{pmatrix} \alpha_1 & \beta_1 & 0 & 0 & 0 \\ 0 & \alpha_2 & \beta_2 & 0 & 0 \\ & \dots & & & \\ 0 & 0 & 0 & \alpha_{k-1} & \beta_{k-1} \\ 0 & 0 & 0 & 0 & \alpha_k \end{pmatrix}$$
 (2.3)

Note here  $||v|| = \sqrt{\sum_i |v_i|^2}$ .

### Algorithm 1 Lanczos bidiagonalization

```
A = C^{m \times n}
\mathbf{v}_1 \text{ is an n-vectors satisfying } ||\mathbf{v}_1|| = 1.
\mathbf{for } i = 1 \text{ to } k \text{ do}
\mathbf{if } i > 1 \text{ then}
\mathbf{v}_i = \mathbf{p}/\beta_{i-1}.
\mathbf{end if}
\mathbf{r} = A\mathbf{v}_i - \beta_{i-1}\mathbf{u}_{i-1}.
\alpha_i = ||\mathbf{r}||.
\mathbf{u}_i = \mathbf{r}/\alpha_i.
\mathbf{if } i < k \text{ then}
\mathbf{p} = A^{\dagger}\mathbf{u}_i - \alpha_i\mathbf{v}_i
\beta_i = ||\mathbf{p}||
\mathbf{end if}
```

It is expected that  $\beta$  approaches zero, if  $\beta = 0$ , than  $A = UTV^{\dagger}$ .

Although the B obtained is not a diagonal matrix, the goal has been archived, and we do not further diagonalize it.