



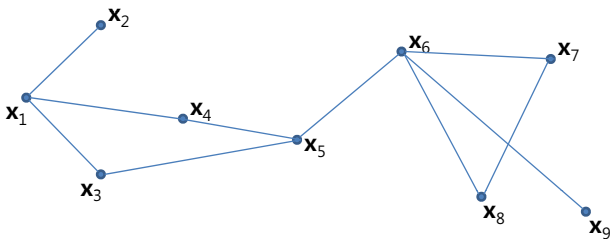
# A Unified Approach to Clustering and Ordering via a Graph Theory

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## 1.1 Clustering and Hubbing



$x_i$  : vertex ( $p$ -vector,  $i = 1, \dots, n$ )

$a_{ij}$  : closeness (adjacency, connectivity) between  $x_i$  and  $x_j$

$a_{ij} = a_{ji}$  : undirected;  $a_{ij} \neq a_{ji}$  : directed

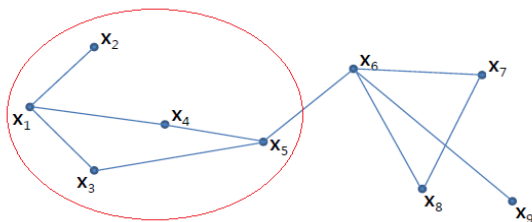
$a_{ij} = 0$  or  $1$  : unweighted;  $a'_{ij}$ 's are different : weighted

$\mathbf{A} = (a_{ij})$  : adjacency matrix



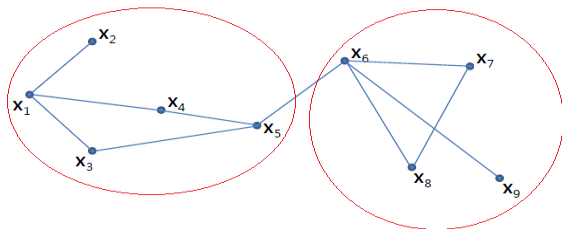
# 1. Motivation

## 1.1 Clustering and Hubbing



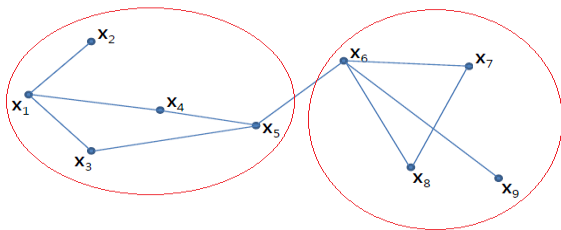
# 1. Motivation

## 1.1 Clustering and Hubbing



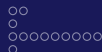
# 1. Motivation

## 1.1 Clustering and Hubbing



$\mathbf{A} = (a_{ij})$  : symmetric (undirected) and weighted with  
 $a_{ii} = 0, \forall i$

goal : grouping objects with similar characteristics, and  
 finding hub in each group



## 1.1 Clustering and Hubbing

- ▶  $z_i$  : unknown index of the object  $\mathbf{x}_i$

If  $z_i = z_j$ , then  $\mathbf{x}_i$  and  $\mathbf{x}_j$  are in the same group. Therefore, clustering is finding  $\mathbf{z} = (z_1, \dots, z_n)$ .

(e.g)  $z_1 = z_2 = \dots = z_5, \quad z_6 = z_7 = z_8 = z_9$

- ▶ If  $\mathbf{x}_i$  is a hub in a group, then  $z_i$  must be much different from  $z_j$ 's,  $j \neq i$  in that group.

Therefore, finding a hub is also finding  $\mathbf{z} = (z_1, \dots, z_n)$ .

(e.g)  $z_6 = 0.8, \quad \text{other } z_j$ 's are almost 0.

## 1.2 Loci Ordering

$g_i, i = 1, \dots, n$  : genes on a chromosome

$a_{ij}$  : recombination fraction between  $g_i$  and  $g_j$

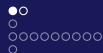
$\mathbf{A} = (a_{ij})$  : symmetric and weighted with  $a_{ii} = 0, \forall i$

- ▶ goal : order genes on a chromosome

$z_i$  : unknown index of the gene  $g_i$

Loci ordering is ordering of  $z_i$ 's

(e.g)  $z_1 > z_2 > \dots > z_n$

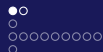


## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?



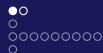


## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

$$(z_i - z_j)^2 a_{ij}$$



## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

$$Q = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij}$$

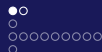


## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

$$Q = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1)$$

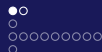


## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

$$\begin{aligned}
 Q &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 \sum_{j=1}^n a_{ij} - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1)
 \end{aligned}$$

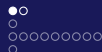


## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

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 Q &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 \sum_{j=1}^n a_{ij} - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 d_i - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad d_i = \sum_{j=1}^n a_{ij}
 \end{aligned}$$



## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

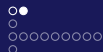
$$\begin{aligned}
 Q &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 \sum_{j=1}^n a_{ij} - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 d_i - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad d_i = \sum_{j=1}^n a_{ij} \\
 &= \mathbf{z}'\mathbf{D}\mathbf{z} - \mathbf{z}'\mathbf{A}\mathbf{z} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad \mathbf{D} = \text{diag}(d_1, \dots, d_n)
 \end{aligned}$$

## 2. Estimation of $\mathbf{z}$

### 2.1 Theory

How to find  $\mathbf{z} = (z_1, \dots, z_n)'$  ?

$$\begin{aligned}
 Q &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (z_i - z_j)^2 a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 \sum_{j=1}^n a_{ij} - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1) \\
 &= \sum_{i=1}^n z_i^2 d_i - \sum_{j=1}^n \sum_{i=1}^n z_i z_j a_{ij} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad d_i = \sum_{j=1}^n a_{ij} \\
 &= \mathbf{z}'\mathbf{D}\mathbf{z} - \mathbf{z}'\mathbf{A}\mathbf{z} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad \mathbf{D} = \text{diag}(d_1, \dots, d_n) \\
 &= \mathbf{z}'\mathbf{L}\mathbf{z} - \lambda(\mathbf{z}'\mathbf{z} - 1), \quad \mathbf{L} = \mathbf{D} - \mathbf{A} : \text{Laplacian matrix}
 \end{aligned}$$



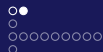
## 2.1 Theory

$$\frac{\partial Q}{\partial z} = 2\mathbf{L}z - 2\lambda z = \mathbf{0}$$

$$\mathbf{L}z = \lambda z$$

$$z'\mathbf{L}z = \lambda$$





## 2.1 Theory

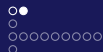
$$\frac{\partial Q}{\partial \mathbf{z}} = 2\mathbf{Lz} - 2\lambda\mathbf{z} = \mathbf{0}$$

$$\mathbf{Lz} = \lambda\mathbf{z}$$

$$\mathbf{z}'\mathbf{Lz} = \lambda$$

$$0 = \lambda_1 < \lambda_2 < \dots < \lambda_n$$

$\mathbf{z}_2$  : Fiedler vector  $\Rightarrow$  clustering (Eigenvector corresponding to non-zero smallest eigenvalue)



## 2.1 Theory

$$\frac{\partial Q}{\partial \mathbf{z}} = 2\mathbf{L}\mathbf{z} - 2\lambda\mathbf{z} = \mathbf{0}$$

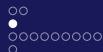
$$\mathbf{L}\mathbf{z} = \lambda\mathbf{z}$$

$$\mathbf{z}'\mathbf{L}\mathbf{z} = \lambda$$

$$0 = \lambda_1 < \lambda_2 < \dots < \lambda_n$$

$\mathbf{z}_2$  : Fiedler vector  $\Rightarrow$  clustering (Eigenvector corresponding to non-zero smallest eigenvalue)

$\mathbf{z}_n \Rightarrow$  hubbing



## 2.2 Relevant Works

- Dempster (1972, Biometrics) : inverse of covariance matrix
- Kim et al. (2008, PNAS) : clustering and classification via graph theory
- Peng et al. (2009, JASA) : variable selection in the inverse of covariance matrix
- Lee and Wasserman (2010, JASA) spectral kernel methods

## 2.3 Artificial Examples

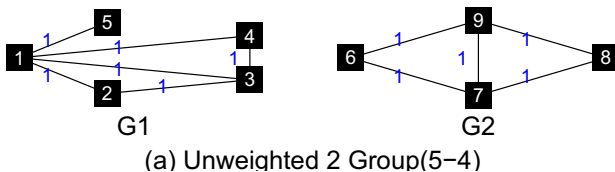
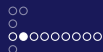


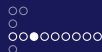
Figure 1. Graph example for matrix representation



## 2.3 Artificial Examples

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{pmatrix} \quad \mathbf{D} = \begin{pmatrix} 4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 3 \end{pmatrix}$$

$$\mathbf{L} = \begin{pmatrix} 4 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & -1 & 2 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & -1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & 3 \end{pmatrix}$$

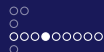


## 2.3 Artificial Examples

$$L = \begin{pmatrix} 4 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & -1 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & -1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & 3 \end{pmatrix}$$

Table 2.1 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 1(a) in Figure 1. (*noise* = 0.0)

Eigenvalues	5.00	4.00	4.00	4.00	2.00	2.00	1.00	0.00	0.00
1	0.89	0.00	0.00	0.00	0.00	0.00	0.00	-0.45	0.00
2	-0.22	0.00	0.00	0.41	0.00	0.71	-0.29	-0.45	0.00
3	-0.22	0.00	0.00	-0.82	0.00	0.00	-0.29	-0.45	0.00
4	-0.22	0.00	0.00	0.41	0.00	-0.71	-0.29	-0.45	0.00
5	-0.22	0.00	0.00	0.00	0.00	0.00	0.87	-0.45	0.00
6	0.00	0.50	0.00	0.00	0.71	0.00	0.00	0.00	-0.50
7	0.00	-0.50	-0.71	0.00	0.00	0.00	0.00	0.00	-0.50
8	0.00	0.50	0.00	0.00	-0.71	0.00	0.00	0.00	-0.50
9	0.00	-0.50	0.71	0.00	0.00	0.00	0.00	0.00	-0.50

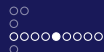


## 2.3 Artificial Examples

$$L = \begin{pmatrix} 4.4 & -1 & -1 & -1 & -1 & -0.1 & -0.1 & -0.1 & -0.1 \\ -1 & 2.4 & -1 & 0 & 0 & -0.1 & -0.1 & -0.1 & -0.1 \\ -1 & -1 & 3.4 & -1 & 0 & -0.1 & -0.1 & -0.1 & -0.1 \\ -1 & 0 & -1 & 2.4 & 0 & -0.1 & -0.1 & -0.1 & -0.1 \\ -1 & 0 & 0 & 0 & 1.4 & -0.1 & -0.1 & -0.1 & -0.1 \\ -0.1 & -0.1 & -0.1 & -0.1 & -0.1 & 2.5 & -1 & 0 & -1 \\ -0.1 & -0.1 & -0.1 & -0.1 & -0.1 & -1 & 3.5 & -1 & -1 \\ -0.1 & -0.1 & -0.1 & -0.1 & -0.1 & 0 & -1 & 2.5 & -1 \\ -0.1 & -0.1 & -0.1 & -0.1 & -0.1 & -1 & -1 & -1 & 3.5 \end{pmatrix}$$

Table 2.2 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 1(a) in Figure 1. (*noise* = 0.1)

Eigenvalues	5.40	4.50	4.50	4.40	2.50	2.40	1.40	0.90	0.00
1	0.89	0.00	0.00	0.00	0.00	0.00	0.00	-0.30	-0.33
2	-0.22	0.00	0.00	0.41	0.00	0.71	0.29	-0.30	-0.33
3	-0.22	0.00	0.00	-0.82	0.00	0.00	0.29	-0.30	-0.33
4	-0.22	0.00	0.00	0.41	0.00	-0.71	0.29	-0.30	-0.33
5	-0.22	0.00	0.00	0.00	0.00	0.00	-0.87	-0.30	-0.33
6	0.00	-0.05	-0.50	0.00	0.71	0.00	0.00	0.37	-0.33
7	0.00	-0.65	0.57	0.00	0.00	0.00	0.00	0.37	-0.33
8	0.00	-0.05	-0.50	0.00	-0.71	0.00	0.00	0.37	-0.33
9	0.00	0.76	0.42	0.00	0.00	0.00	0.00	0.37	-0.33



## 2.3 Artificial Examples

$$L = \begin{pmatrix} 4.8 & -1 & -1 & -1 & -1 & -0.2 & -0.2 & -0.2 & -0.2 \\ -1 & 2.8 & -1 & 0 & 0 & -0.2 & -0.2 & -0.2 & -0.2 \\ -1 & -1 & 3.8 & -1 & 0 & -0.2 & -0.2 & -0.2 & -0.2 \\ -1 & 0 & -1 & 2.8 & 0 & -0.2 & -0.2 & -0.2 & -0.2 \\ -1 & 0 & 0 & 0 & 1.8 & -0.2 & -0.2 & -0.2 & -0.2 \\ -0.2 & -0.2 & -0.2 & -0.2 & -0.2 & 3.0 & -1 & 0 & -1 \\ -0.2 & -0.2 & -0.2 & -0.2 & -0.2 & -1 & 4.0 & -1 & -1 \\ -0.2 & -0.2 & -0.2 & -0.2 & -0.2 & 0 & -1 & 3.0 & -1 \\ -0.2 & -0.2 & -0.2 & -0.2 & -0.2 & -1 & -1 & -1 & 4.0 \end{pmatrix}$$

Table 2.3 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 1(a) in Figure 1. ( $noise = 0.2$ )

Eigenvalues	5.80	5.00	5.00	4.80	...	1.80	0.00
1	0.89	0.00	0.00	0.00	...	0.00	-0.33
2	-0.22	0.00	0.00	-0.41	...	-0.29	-0.33
3	-0.22	0.00	0.00	0.82	...	-0.29	-0.33
4	-0.22	0.00	0.00	-0.41	...	-0.29	-0.33
5	-0.22	0.00	0.00	0.00	...	0.87	-0.33
6	0.00	-0.23	-0.44	0.00	...	0.00	-0.33
7	0.00	-0.40	0.77	0.00	...	0.00	-0.33
8	0.00	-0.23	-0.44	0.00	...	0.00	-0.33
9	0.00	0.86	0.12	0.00	...	0.00	-0.33





## 2.3 Artificial Examples

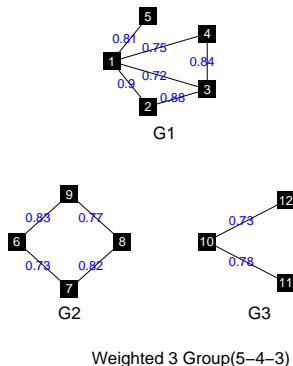
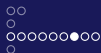


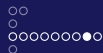
Figure 2. Graph example for matrix representation



## 2.3 Artificial Examples

Table 2.4 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 2 in Figure 2. ( $noise = 0.0$ )

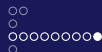
Eigenvalues	4.00	3.32	3.15	2.27	...	0.75	0.00	0.00	0.00
1	0.88	0.14	0.00	0.00	...	0.00	0.45	0.00	0.00
2	-0.32	0.40	0.00	0.00	...	0.00	0.45	0.00	0.00
3	-0.10	-0.84	0.00	0.00	...	0.00	0.45	0.00	0.00
4	-0.24	0.35	0.00	0.00	...	0.00	0.45	0.00	0.00
5	-0.22	-0.04	0.00	0.00	...	0.00	0.45	0.00	0.00
6	0.00	0.00	0.49	0.00	...	0.00	0.00	-0.50	0.00
7	0.00	0.00	-0.48	0.00	...	0.00	0.00	-0.50	0.00
8	0.00	0.00	0.51	0.00	...	0.00	0.00	-0.50	0.00
9	0.00	0.00	-0.52	0.00	...	0.00	0.00	-0.50	0.00
10	0.00	0.00	0.00	0.82	...	-0.02	0.00	0.00	0.58
11	0.00	0.00	0.00	-0.43	...	-0.70	0.00	0.00	0.58
12	0.00	0.00	0.00	-0.39	...	0.72	0.00	0.00	0.58



## 2.3 Artificial Examples

Table 2.5 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 2 in Figure 2. ( $noise = 0.1$ )

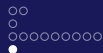
Eigenvalues	4.70	4.02	3.93	3.17	...	1.17	0.00
1	0.88	-0.14	0.00	0.00	...	-0.30	-0.28
2	-0.32	-0.40	0.06	0.00	...	-0.32	-0.27
3	-0.10	0.84	-0.16	0.00	...	-0.30	-0.28
4	-0.24	-0.35	0.08	0.00	...	-0.29	-0.29
5	-0.22	0.04	0.00	0.00	...	-0.27	-0.29
6	0.00	0.00	-0.46	0.00	...	0.39	-0.30
7	0.00	0.00	0.48	0.00	...	0.37	-0.29
8	0.00	0.00	-0.51	0.00	...	0.36	-0.29
9	0.00	0.00	0.51	0.00	...	0.37	-0.29
10	0.00	0.00	0.00	-0.82	...	0.00	-0.29
11	0.00	0.00	0.00	0.43	...	0.00	-0.29
12	0.00	0.00	0.00	0.39	...	0.00	-0.29



## 2.3 Artificial Examples

Table 2.6 Eigenvalues and eigenvectors for the Laplacian matrix of the combined graphs 2 in Figure 2. ( $noise = 0.2$ )

Eigenvalues	5.40	4.72	4.71	4.07	...	2.20	0.00
1	0.88	0.14	0.10	0.00	...	0.01	0.29
2	-0.32	0.40	0.35	0.00	...	-0.26	0.27
3	-0.10	-0.84	-0.76	0.00	...	-0.30	0.28
4	-0.24	0.35	0.33	0.00	...	-0.31	0.29
5	-0.22	-0.04	-0.03	0.00	...	0.86	0.29
6	0.00	0.00	-0.19	0.00	...	0.00	0.31
7	0.00	0.00	0.21	0.00	...	0.00	0.29
8	0.00	0.00	-0.22	0.00	...	0.00	0.29
9	0.00	0.00	0.22	0.00	...	0.00	0.29
10	0.00	0.00	0.00	-0.82	...	0.00	0.29
11	0.00	0.00	0.00	0.43	...	0.00	0.29
12	0.00	0.00	0.00	0.39	...	0.00	0.29



## 2.4 Hard-thresholding

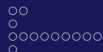
observed value

= deterministic part + noise part

To remove noise, use the idea of shrinkage

Here, we use hard-thresholding functions given by

$t_H(x) = x I(|x| > \delta)$ , where  $\delta > 0$  is a thresholding parameter to be estimated.



## 3. Locus Ordering

### 3.1 Introduction

#### (1) Locus

*chromosome location of a gene*

#### (2) Locus Ordering

- *a linear arrangement of genes or genetic markers in a linkage group*
- *necessary step in constructing genetic map*
- *one of the most important issue in genetic research area*



## 3.1 Introduction

1 1.1. Introduction

2 1.2. Estimation of  $z$

3 1.3. Example

4 1.4. Extensions

5 1.5. Summary

6 1.6. References

7 1.7. Appendix

8 1.8. Bibliography

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15 1.15. License

16 1.16. Disclaimer

17 1.17. Privacy Policy

18 1.18. Terms of Service

19 1.19. Cookies

20 1.20. Security

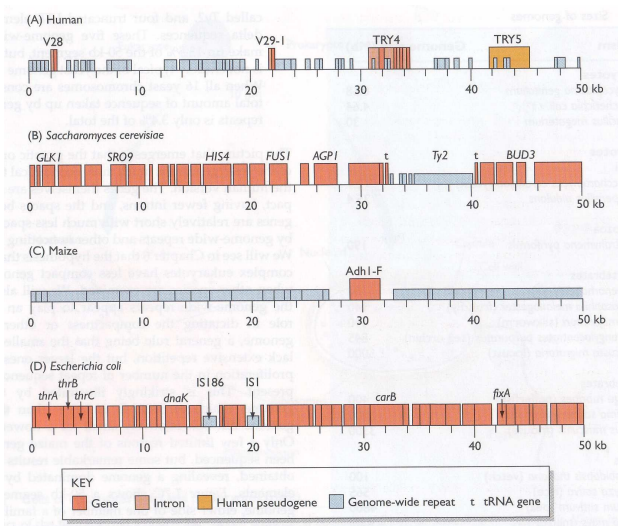
21 1.21. Updates

22 1.22. Feedback

X 1.23. Error Report



## 3.1 Introduction







### (3) Crossover

- *As meiosis (cell division leading to the formation of gametes) progresses, crossover might occur at chiasmata.*
- *The chance of crossover is low when two loci are closely located, and it is high when they are apart.*
- *An odd number of crossover between two loci leads to a recombination.*
- *Therefore, recombination fraction, the ratio of recombinant gametes to total gametes, is a measure of distance between two loci.*

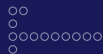


### (3) Crossover

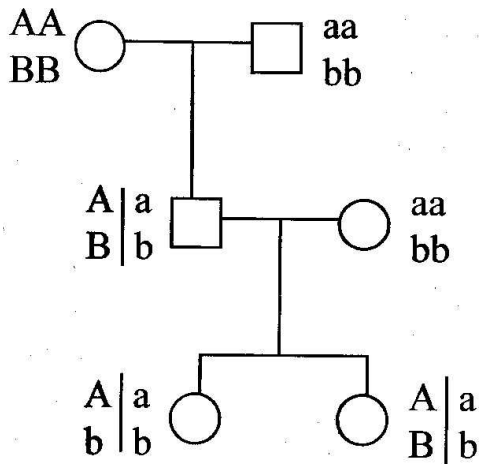
$$r_{ij}, \quad 1 \leq i < j \leq n$$

: two-point recombination fractions for a pair of loci  $i$  and  $j$

If two loci  $i$  and  $j$  are closely located, i.e., tightly linked, then  $r_{ij}$  is close to 0, and if not it is away from 0.

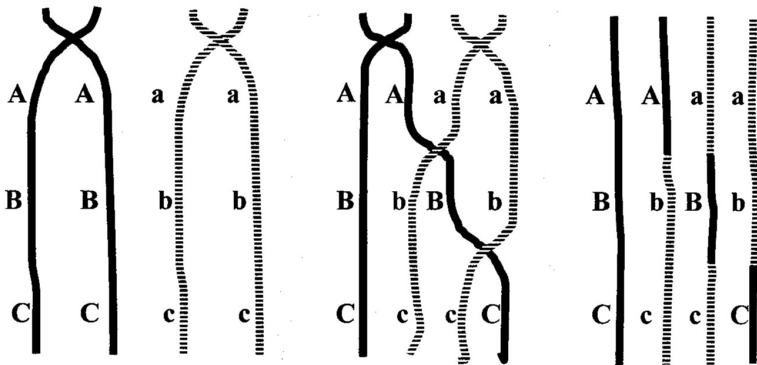


## 3.1 Introduction





## 3.1 Introduction



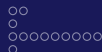


## (4) Computational issues

*With  $n$  loci, there are  $n!/2$  possible orderings if the orientation of the orders is ignored.*

*10 loci : 1,814,000 possible orders*

*If analysis of each order takes 1 second (it might take more than that), evaluating all orders requires 21 days of uninterrupted computation.*



## (5) Existing methods

- ▶ *Falk(1989) : minimum sum of adjacent recombination fractions*
- ▶ *Weeks and Lange(1987) : maximum sum of adjacent lod scores*
- ▶ *Knapp et al. (1989) : minimum sum of the probability of double recombinants*
- ▶ *Lander and Green (1987) : maximum likelihood*
- ▶ *Thompson (1989) : minimum obligatory crossovers*
- ▶ *Kammerer and MacCluer(1988) and Olson and Boehnke(1990) : Comparisons between those methods when the number of loci is 6 or 7.*
- ▶ *Weeks(1991) : overview in locus ordering.*

## 3.2 Algorithm

### (1) Notations

*For example,*

*if  $\mathbf{z} = (-1/\sqrt{5}, 0, 1/\sqrt{5}, -\sqrt{2}/\sqrt{5}, \sqrt{2}/\sqrt{5})$ ,*

*then the resulting order is 4 – 1 – 2 – 3 – 5*

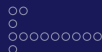
*or 5 – 3 – 2 – 1 – 4.*

## (2) Estimation of the thresholding parameter $\delta$

- (i) *As  $\delta$  increases  $\lambda_2$  decreases*
- (ii) *We get more information as  $\lambda_2$  becomes smaller*
- (iii) *If  $\delta$  is too large, then  $\lambda_2$  will be zero so that we lose all the information.*
- (iv) *To solve this contradicting situation, we consider  $\lambda_3$ . Since the eigenvectors  $\mathbf{z}_2$  and  $\mathbf{z}_3$  are orthogonal, the information contained in  $\mathbf{z}_3$  is independent on the information contained in  $\mathbf{z}_2$ . Therefore, it is desirable that  $\lambda_2$  must be relatively small compared to  $\lambda_3$ . Then, most of locus ordering information is contained in the corresponding eigenvector  $\mathbf{z}_2$ . Choose  $\delta$  maximizing*

$$\Lambda = \lambda_3 / \lambda_2.$$





## (2) Accuracy of Locus Ordering

$$\mathbf{t} = (t(1), \dots, t(n))$$

:  $t(i)$  denote the true order of the  $i$ th gene

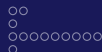
$$\mathbf{e} = (e(1), \dots, e(n))$$

:  $e(i)$  denote the estimated order of the  $i$ th gene

The accuracy of the estimated order  $\mathbf{e}$

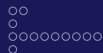
$NCL = \sum_{i=1}^n I(t(i) = e(i))$  : number of correct loci

$PIL = \sum_{i=1}^n |(t(i) - e(i))|$  : penalized incorrect loci



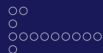
## 3.3 Example

- (1) data : 26 loci of barley chromosome IV generated by the North American Barley Genome Mapping Project (NABGMP)
- (2) recombination fraction matrix for 26 loci :
- (3) Based on the several preliminary locus ordering method it has been known that the best ordering for the 26 loci is  $1, 2, \dots, 26$



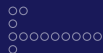
## 3.3 Example

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	.00	.89	.16	.29	.31	.43	.41	.44	.44	.46	.49	.48	.49
2	.89	.00	.95	.81	.79	.69	.71	.66	.65	.63	.63	.62	.62
3	.16	.95	.00	.87	.86	.76	.78	.73	.72	.71	.70	.69	.68
4	.29	.81	.87	.00	.96	.89	.90	.86	.86	.84	.81	.81	.79
5	.31	.79	.86	.96	.00	.90	.89	.83	.82	.83	.82	.80	.80
6	.43	.69	.76	.89	.90	.00	.99	.93	.95	.93	.92	.91	.87
7	.41	.71	.78	.90	.89	.99	.00	.92	.92	.92	.90	.89	.86
8	.44	.66	.73	.86	.83	.93	.92	.00	.99	.98	.93	.94	.91
9	.44	.65	.72	.86	.82	.95	.92	.99	.00	.99	.95	.93	.92
10	.46	.63	.71	.84	.83	.93	.92	.98	.99	.00	.97	.96	.93
11	.49	.63	.70	.81	.82	.92	.90	.93	.95	.97	.00	.98	.96
12	.48	.62	.69	.81	.80	.91	.89	.94	.93	.96	.98	.00	.95
13	.49	.62	.68	.79	.80	.87	.86	.91	.92	.93	.96	.95	.00
14	.47	.65	.70	.82	.81	.90	.89	.94	.94	.96	.98	.98	.96
15	.44	.67	.72	.82	.81	.88	.87	.92	.92	.92	.93	.96	.93
16	.41	.67	.68	.73	.76	.82	.81	.87	.86	.88	.90	.89	.86
17	.45	.60	.63	.68	.67	.74	.72	.78	.77	.79	.78	.79	.77
18	.48	.57	.59	.64	.62	.69	.69	.72	.72	.74	.74	.72	.74
19	.51	.52	.50	.52	.51	.53	.52	.58	.59	.59	.61	.62	.63
20	.52	.51	.51	.52	.53	.57	.56	.59	.60	.60	.63	.63	.64
21	.52	.52	.51	.51	.51	.52	.53	.56	.56	.57	.60	.60	.61
22	.52	.52	.51	.51	.50	.54	.53	.55	.56	.57	.60	.59	.60
23	.52	.53	.52	.52	.51	.53	.54	.56	.57	.57	.60	.59	.61
24	.54	.50	.49	.50	.48	.52	.52	.53	.55	.56	.60	.59	.60
25	.54	.50	.50	.53	.52	.53	.52	.55	.56	.57	.59	.58	.61
26	.57	.48	.47	.49	.47	.50	.51	.53	.54	.52	.57	.57	.60



## 3.3 Example

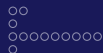
	14	15	16	17	18	19	20	21	22	23	24	25	26
1	.47	.44	.41	.45	.48	.51	.52	.52	.52	.52	.54	.54	.57
2	.65	.67	.67	.60	.57	.52	.51	.52	.52	.53	.50	.50	.48
3	.70	.72	.68	.63	.59	.50	.51	.51	.51	.52	.49	.50	.47
4	.82	.82	.73	.68	.64	.52	.52	.51	.51	.52	.50	.53	.49
5	.81	.81	.76	.67	.62	.51	.53	.51	.50	.51	.48	.52	.47
6	.90	.88	.82	.74	.69	.53	.57	.52	.54	.53	.52	.53	.50
7	.89	.87	.81	.72	.69	.52	.56	.53	.53	.54	.52	.52	.51
8	.94	.92	.87	.78	.72	.58	.59	.56	.55	.56	.53	.55	.53
9	.94	.92	.86	.77	.72	.59	.60	.56	.56	.57	.55	.56	.54
10	.96	.92	.88	.79	.74	.59	.60	.57	.57	.57	.56	.57	.52
11	.98	.93	.90	.78	.74	.61	.63	.60	.60	.60	.60	.59	.57
12	.98	.96	.89	.79	.72	.62	.63	.60	.59	.59	.59	.58	.57
13	.96	.93	.86	.77	.74	.63	.64	.61	.60	.61	.60	.61	.60
14	.00	.97	.90	.79	.76	.61	.62	.59	.58	.58	.58	.59	.57
15	.97	.00	.92	.83	.80	.62	.63	.60	.59	.59	.59	.59	.57
16	.90	.92	.00	.88	.82	.67	.69	.66	.66	.62	.63	.62	.62
17	.79	.83	.88	.00	.93	.77	.77	.76	.73	.72	.73	.72	.70
18	.76	.80	.82	.93	.00	.82	.84	.82	.81	.78	.80	.78	.76
19	.61	.62	.67	.77	.82	.00	.97	.92	.93	.93	.95	.91	.89
20	.62	.63	.69	.77	.84	.97	.00	.98	.98	.96	.97	.93	.89
21	.59	.60	.66	.76	.82	.92	.98	.00	1.00	.98	.99	.93	.91
22	.58	.59	.66	.73	.81	.93	.98	1.00	.00	.98	.99	.95	.92
23	.58	.59	.62	.72	.78	.93	.96	.98	.98	.00	.99	.92	.91
24	.58	.59	.63	.73	.80	.95	.97	.99	.99	.99	.00	.96	.93
25	.59	.59	.62	.72	.78	.91	.93	.93	.95	.92	.96	.00	.92
26	.57	.57	.62	.70	.76	.89	.89	.91	.92	.91	.93	.92	.00



## 3.3 Example

$$\delta = 0, \quad \lambda_2 = 12.16, \quad \lambda_3 = 14.72, \quad \Lambda = 1.21$$

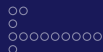
true order	Z	predicted order	diff	C. I.	
1	0.9695	1	0	1-1	O
2	0.0429	2	0	2-2	O
3	-0.1153	26	23	3-3	X
4	-0.0791	25	21	4-5	X
5	-0.0788	24	19	4-5	X
6	-0.0558	22	16	6-7	X
7	-0.0589	23	16	6-7	X
8	-0.0520	21	13	8-11	X
9	-0.0518	20	11	8-11	X
10	-0.0492	17	7	8-13	X
11	-0.0440	14	3	11-15	O
12	-0.0458	15	3	11-15	O
13	-0.0431	13	0	11-15	O
14	-0.0459	16	2	11-15	X
15	-0.0506	18	3	11-15	X
16	-0.0507	19	3	16-16	X
17	-0.0423	12	5	17-17	X
18	-0.0347	11	7	18-18	X
19	-0.0193	10	9	19-24	X
20	-0.0187	9	11	19-25	X
21	-0.0164	8	13	19-25	X
22	-0.0159	7	15	19-25	X
23	-0.0159	6	17	19-25	X
24	-0.0110	4	20	19-25	X
25	-0.0127	5	20	19-25	X
26	-0.0035	3	23	25-26	X



## 3.3 Example

$$\delta = 0.1, \quad \lambda_2 = 12.16, \quad \lambda_3 = 14.72, \quad \Lambda = 1.21$$

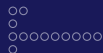
true order	Z	predicted order	diff	C. I.	
1	0.9695	1	0	1-1	O
2	0.0429	2	0	2-2	O
3	-0.1153	26	23	3-3	X
4	-0.0791	25	21	4-5	X
5	-0.0788	24	19	4-5	X
6	-0.0558	22	16	6-7	X
7	-0.0589	23	16	6-7	X
8	-0.0520	21	13	8-11	X
9	-0.0518	20	11	8-11	X
10	-0.0492	17	7	8-13	X
11	-0.0440	14	3	11-15	O
12	-0.0458	15	3	11-15	O
13	-0.0431	13	0	11-15	O
14	-0.0459	16	2	11-15	X
15	-0.0506	18	3	11-15	X
16	-0.0507	19	3	16-16	X
17	-0.0423	12	5	17-17	X
18	-0.0347	11	7	18-18	X
19	-0.0193	10	9	19-24	X
20	-0.0187	9	11	19-25	X
21	-0.0164	8	13	19-25	X
22	-0.0159	7	15	19-25	X
23	-0.0159	6	17	19-25	X
24	-0.0110	4	20	19-25	X
25	-0.0127	5	20	19-25	X
26	-0.0035	3	23	25-26	X



## 3.3 Example

$$\delta = 0.5, \quad \lambda_2 = 5.14, \quad \lambda_3 = 13.01, \quad \Lambda = 2.53$$

true order	Z	predicted order	diff	C.I.	
1	0.9701	1	0	1-1	O
2	0.0184	2	0	2-2	O
3	-0.0670	25	22	3-3	X
4	-0.0641	24	20	4-5	X
5	-0.0673	26	21	4-5	X
6	-0.0613	23	17	6-7	X
7	-0.0612	22	15	6-7	X
8	-0.0605	21	13	8-11	X
9	-0.0602	20	11	8-11	X
10	-0.0602	19	9	8-13	X
11	-0.0591	16	5	11-15	X
12	-0.0593	17	5	11-15	X
13	-0.0587	14	1	11-15	O
14	-0.0593	18	4	11-15	X
15	-0.0590	15	0	11-15	O
16	-0.0572	13	3	16-16	X
17	-0.0545	12	5	17-17	X
18	-0.0524	11	7	18-18	X
19	-0.0075	10	9	19-24	X
20	-0.0075	9	11	19-25	X
21	-0.0059	8	13	19-25	X
22	-0.0056	7	15	19-25	X
23	-0.0054	6	17	19-25	X
24	0.0012	4	20	19-25	X
25	-0.0039	5	20	19-25	X
26	0.0085	3	23	25-26	X

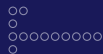


## 3.3 Example

$$\delta = 0.58, \quad \lambda_2 = 0.85, \quad \lambda_3 = 5.62, \quad \Lambda = 6.61$$

true order	Z	predicted order	diff	C.I.	
1	0.9766	1	0	1-1	○
2	0.0451	2	0	2-2	○
3	-0.0349	3	0	3-3	○
4	-0.0362	4	0	4-5	○
5	-0.0363	5	0	4-5	○
6	-0.0372	6	0	6-7	○
7	-0.0370	7	0	6-7	○
8	-0.0379	8	0	8-11	○
9	-0.0383	9	0	8-11	○
10	-0.0385	10	0	8-13	○
11	-0.0403	12	1	11-15	○
12	-0.0401	14	2	11-15	○
13	-0.0408	11	2	11-15	○
14	-0.0402	15	1	11-15	○
15	-0.0402	13	2	11-15	○
16	-0.0409	16	0	16-16	○
17	-0.0417	17	0	17-17	○
18	-0.0450	18	0	18-18	○
19	-0.0484	19	0	19-24	○
20	-0.0479	20	0	19-25	○
21	-0.0494	21	0	19-25	○
22	-0.0495	22	0	19-25	○
23	-0.0495	23	0	19-25	○
24	0.0495	24	0	19-25	○
25	-0.0500	25	0	19-25	○
26	0.0520	26	0	25-26	○

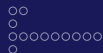




## 3.3 Example

$$\delta = 0.6, \quad \lambda_2 = 0.85, \quad \lambda_3 = 3.77, \quad \Lambda = 4.44$$

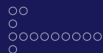
true order	Z	predicted order	diff	C.I.
1	0.9757	1	0	1-1 O
2	0.0475	2	0	2-2 O
3	-0.0314	3	0	3-3 O
4	-0.0335	4	0	4-5 O
5	-0.0336	5	0	4-5 O
6	-0.0345	7	1	6-7 O
7	-0.0343	6	1	6-7 O
8	-0.0348	8	0	8-11 O
9	-0.0348	9	0	8-11 O
10	-0.0350	10	0	8-13 O
11	-0.0377	14	3	11-15 O
12	-0.0364	13	1	11-15 O
13	-0.0402	15	2	11-15 O
14	-0.0363	12	2	11-15 O
15	-0.0362	11	4	11-15 O
16	-0.0404	16	0	16-16 O
17	-0.0416	17	0	17-17 O
18	-0.0457	18	0	18-18 O
19	-0.0516	20	1	19-24 O
20	-0.0516	19	1	19-25 O
21	-0.0545	21	0	19-25 O
22	-0.0546	22	0	19-25 O
23	-0.0558	24	1	19-25 O
24	-0.0557	23	1	19-25 O
25	-0.0558	25	0	19-25 O
26	-0.0559	26	0	25-26 O



## 3.3 Example

$$\delta = 0.8, \quad \lambda_2 = 0.23, \quad \lambda_3 = 0.52, \quad \Lambda = 2.26$$

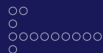
true order	$Z$	predicted order	$ diff $	C.I.	
1	0.3229	1	0	1-1	O
2	0.2391	2	0	2-2	O
3	0.1881	3	0	3-3	O
4	0.1391	4	0	4-5	O
5	0.1305	5	0	4-5	O
6	0.1226	7	1	6-7	O
7	0.1227	6	1	6-7	O
8	0.1223	9	1	8-11	O
9	0.1223	8	1	8-11	O
10	0.1222	10	0	8-13	O
11	0.1221	11	0	11-15	O
12	0.1221	12	0	11-15	O
13	0.1209	14	1	11-15	O
14	0.1220	13	1	11-15	O
15	0.0989	15	0	11-15	O
16	0.0917	16	0	16-16	O
17	0.0116	17	0	17-17	O
18	-0.1445	18	0	18-18	O
19	-0.2668	20	1	19-24	O
20	-0.2666	19	1	19-25	O
21	-0.2670	21	0	19-25	O
22	-0.2671	22	0	19-25	O
23	-0.2805	24	1	19-25	O
24	-0.2673	23	1	19-25	O
25	-0.2808	25	0	19-25	O
26	-0.2810	26	0	25-26	O



## 3.3 Example

$$\delta = 0.83, \quad \lambda_2 = 0.06, \quad \lambda_3 = 1.16, \quad \Lambda = 19.33$$

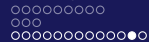
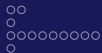
true order	$Z$	predicted order	$ diff $	C.I.	
1	0.2856	1	0	1-1	O
2	0.2855	2	0	2-2	O
3	0.2854	5	2	3-3	X
4	0.2854	7	3	4-5	X
5	0.2854	3	2	4-5	X
6	0.2675	8	2	6-7	X
7	0.2854	6	1	6-7	O
8	-0.0461	10	2	8-11	O
9	0.1059	9	0	8-11	O
10	0.2854	4	6	8-13	X
11	-0.1286	12	1	11-15	O
12	-0.1354	13	1	11-15	O
13	-0.1260	11	2	11-15	O
14	-0.1355	15	1	11-15	O
15	-0.1355	14	1	11-15	O
16	-0.1355	15	1	16-16	X
17	-0.1368	19	2	17-17	X
18	-0.1362	18	0	18-18	O
19	-0.1436	22	3	19-24	O
20	-0.1361	17	3	19-25	X
21	-0.1378	20	1	19-25	O
22	-0.1378	21	1	19-25	O
23	-0.1640	24	1	19-25	O
24	-0.1459	23	1	19-25	O
25	-0.1885	25	0	19-25	O
26	-0.2021	26	0	25-26	O



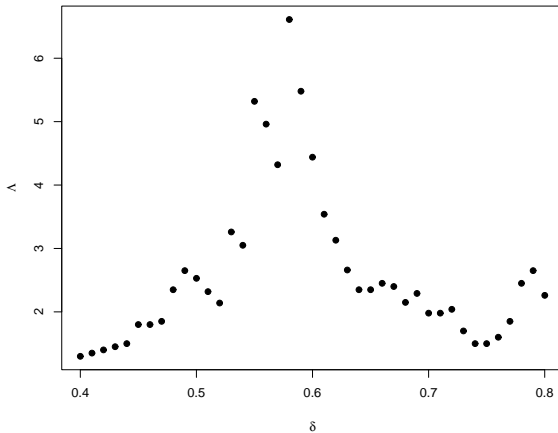
## 3.3 Example

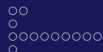
$$\delta = 0.84, \quad \lambda_2 = 0.0003, \quad \lambda_3 = 0.2410, \quad \Lambda = 926.77$$

true order	Z	predicted order	diff	C.I.	
1	0.2942	1	0	1-1	O
2	0.2942	1	1	2-2	X
3	0.2942	1	2	3-3	X
4	0.2942	1	3	4-5	X
5	0.2942	1	4	4-5	X
6	0.2942	1	5	6-7	X
7	0.2942	1	6	6-7	X
8	0.2942	1	7	8-11	X
9	-0.1307	9	0	8-11	O
10	-0.1307	9	1	8-13	O
11	-0.1307	9	2	11-15	X
12	-0.1307	9	3	11-15	X
13	-0.1307	9	4	11-15	X
14	-0.1307	9	5	11-15	X
15	-0.1307	9	6	11-15	X
16	-0.1307	9	7	16-16	X
17	-0.1307	9	8	17-17	X
18	-0.1307	9	9	18-18	X
19	-0.1307	9	10	19-24	X



## 3.3 Example





## 3.3 Example

$\delta$	$\lambda_2$	$\lambda_3$	$\Lambda = \lambda_3/\lambda_2$	NCL	NCLI	$ diff $
0.0	12.16	14.72	1.21	3	5	280
0.1	12.16	14.72	1.21	3	5	280
0.2	11.97	14.71	1.23	3	5	280
0.3	11.63	14.71	1.26	3	5	280
0.4	11.28	14.71	1.30	3	5	280
0.5	5.14	13.01	2.53	3	4	286
0.58	0.85	5.62	6.61	21	26	8
0.6	0.85	3.77	4.44	15	26	18
0.7	0.65	1.29	1.98	13	26	18
0.8	0.23	0.52	2.26	16	26	10
0.82	0.12	0.29	2.42	13	26	20
0.84	0.00026	0.24096	926.77	2	3	181



## 4.1 Cryptology (Alphabet scramble)

## 4. Extensions

## 4.1 Cryptology (Alphabet scramble)

catssitsit  $\implies$  statistics

$a_{ij} = P(i\text{th alphabet coming right before the } j\text{th alphabet})$

$\mathbf{A} = (a_{ij})$  : directed and weighted with

$$\sum_{i=1}^n a_{ij} = \sum_{j=1}^n a_{ij} = 1, \quad \forall i, j$$

goal : Unscramble the scrambled word

Laplacian matrix :  $\mathbf{I} - \mathbf{A}$



## 4.2 Protein Structure

base (A, T, G, C)  $\implies$  amino acid (20 types)  $\implies$  protein

goal : identification and/or classification of new protein