

PROBLEM: Given the training set $\{y_1, y_2, \dots, y_p\}$ of patterns, find W and θ such that

$$o(k+1) = \Gamma(Wo(k) - \theta)$$

Solves problems 1-4 of previous slide.

$$y_i = \begin{pmatrix} y_{i1} \\ \vdots \\ y_{in} \end{pmatrix} \in \mathbb{R}^n$$

OUTER PRODUCT RULE: Related to Hebbian Learning

$$W = \frac{1}{n} (y_1 y_1^T + y_2 y_2^T + \dots + y_p y_p^T) \quad \theta = 0$$

$$= \frac{1}{n} \sum_{i=1}^p y_i y_i^T$$

$\Rightarrow W = W^T$! But $w_{ii} \neq 0$ in general.

Assume that y_i 's are binary vectors ($\Rightarrow y_{ij} = \pm 1$)

$$y_i y_i^T = \begin{pmatrix} \pm 1 \\ \pm 1 \\ \vdots \\ \pm 1 \end{pmatrix} (\pm 1 \dots \pm 1) = \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{pmatrix}$$

\Rightarrow diagonal entries of $\sum_{i=1}^p y_i y_i^T \Rightarrow p$!

\Rightarrow To get $w_{ii} = 0$

$$\Rightarrow \boxed{W = \frac{1}{n} \sum_{i=1}^p y_i y_i^T - \frac{p}{n} I} \quad \theta = 0.$$

\Rightarrow This choice satisfies conditions 3-4.

* Fixed point?

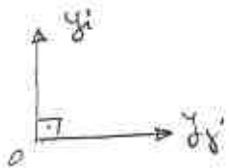
$$\boxed{o(k+1) = \Gamma(w(o(k)))} \quad k=0,1,\dots$$

$o(0) = y_i$. do we have $o(1) = o(2) = \dots = y_i$?

$$\begin{aligned} v(1) = w y_i &= \left(\frac{1}{n} \sum_{j=1}^p y_j y_j^T - \frac{p}{n} I \right) y_i \\ &= \frac{1}{n} (y_i y_i^T y_i + \dots + y_i y_i^T y_i + \dots + y_p y_p^T y_i) - \frac{p}{n} y_i \end{aligned}$$

How do we guarantee that $y_i = \Gamma(w y_i)$?

* Assume that patterns are ORTHOGONAL! $\boxed{y_i^T y_j = 0 \quad i \neq j}$



$$\Rightarrow \boxed{w y_i = \frac{1}{n} y_i \cdot y_i^T y_i - \frac{p}{n} y_i}$$

$$y_i^T y_i = \begin{pmatrix} 1 & & \\ & 1 & \\ & & \dots \\ & & & 1 \end{pmatrix} \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = n$$

$$\Rightarrow \boxed{w y_i = \left(1 - \frac{p}{n}\right) y_i}$$

Result! y_i becomes an EIGENVECTOR of w with an EIGENVALUE $1 - \frac{p}{n}$!

y_i 's are orthogonal $\Rightarrow p \leq n \Rightarrow 1 - \frac{p}{n} \geq 0$.

$$\Rightarrow \boxed{\text{sign}(w y_i) = \text{sign} \left(\left(1 - \frac{p}{n}\right) y_i \right) = \text{sign}(y_i) = y_i !}$$

\Rightarrow All y_i become FIXED POINTS of w !

\Rightarrow Solves problem 1 when patterns are ORTHOGONAL !

NOTE: Since $\theta=0$, $o(k+1) = \Gamma(w o(k))$

$$\Gamma(w y_i) = y_i \iff \Gamma(w (-y_i)) = \Gamma(-w y_i) = -\Gamma(w y_i) = -y_i$$

RESULT: y_i is stored $\iff -y_i$ is stored (False pattern storage)

+ best problem: Minimum of "computational cost"

$$\boxed{E = -\frac{1}{2} o^T w o + \theta^T o = -\frac{1}{2} o^T w o}$$

w is symmetric \Rightarrow All eigenvalues are REAL ($\lambda_1, \lambda_2, \dots, \lambda_n$)

$$\lambda_{\min} = \min \{ \lambda_1, \dots, \lambda_n \}, \quad \lambda_{\max} = \max \{ \lambda_1, \dots, \lambda_n \}$$

$$\Rightarrow \lambda_{\min} \|o\|^2 \leq o^T w o \leq \lambda_{\max} \|o\|^2 \quad \forall o!$$

$$\Rightarrow \boxed{-\frac{\lambda_{\max}}{2} \|o\|^2 \leq -\frac{1}{2} o^T w o \leq -\frac{\lambda_{\min}}{2} \|o\|^2}$$

Eigenvalues of w ?

$$w y_i = \left(1 - \frac{p}{n}\right) y_i \quad i=1, 2, \dots, p \quad \Rightarrow \boxed{\lambda_1 = \lambda_2 = \dots = \lambda_p = 1 - \frac{p}{n}}$$

Rest of the eigenvalues?

Let y_{p+1}, \dots, y_n be ORTHOGONAL COMPLEMENT of $\{y_1, \dots, y_p\}$.

$$\boxed{y_i^T y_j = 0 \quad i=1, 2, \dots, p \quad j=p+1, \dots, n.}$$

$$w y_j = \left(\frac{1}{n} \sum_{i=1}^p y_i y_i^T - \frac{p}{n} I \right) y_j = \frac{1}{n} \sum_{i=1}^p y_i y_i^T y_j - \frac{p}{n} y_j = -\frac{p}{n} y_j$$

$$\Rightarrow \boxed{w y_j = -\frac{p}{n} y_j \quad j=p+1, \dots, n.}$$

$$\Rightarrow \boxed{\lambda_{p+1} = \dots = \lambda_n = -\frac{p}{n}}$$

$$\Rightarrow \boxed{\lambda_{\max} = 1 - \frac{p}{n} > 0}, \quad \boxed{\lambda_{\min} = -\frac{p}{n} < 0}$$

$$\Rightarrow -\left(\frac{1-p}{2}\right) \|0\|^2 \leq -\frac{1}{2} 0^T W_0 \leq +\frac{p}{2n} \|0\|^2$$

But since $0 = \begin{pmatrix} \mp 1 \\ \vdots \\ \mp 1 \end{pmatrix} \Rightarrow \|0\|^2 = (\mp 1 \dots \mp 1) \begin{pmatrix} \mp 1 \\ \vdots \\ \mp 1 \end{pmatrix} = n$

$$\Rightarrow \boxed{\frac{p-n}{2} \leq -\frac{1}{2} 0^T W_0 \leq \frac{p}{2}}$$

$$E(y_i) = -\frac{1}{2} y_i^T W y_i = -\frac{1}{2} y_i^T \left(1 - \frac{p}{n}\right) y_i = -\frac{1}{2} \left(1 - \frac{p}{n}\right) \|y_i\|^2$$

$$= -\frac{1}{2} (n-p) = \frac{p-n}{2} \leftarrow \text{Minimum of } E! \quad (i=1, 2, \dots, p)$$

RESULT: If the patterns are ORTHOGONAL \Rightarrow this design technique satisfies 1-4'

Expectation: If the patterns are NEARLY ORTHOGONAL ($y_i^T y_j \approx 0$) \Rightarrow we expect that the method still works

A TRICK: Let $\{y_1, \dots, y_p\}$ be given with $p < n$.

\Rightarrow Make a transform $y_i \leftrightarrow \hat{y}_i$ such that \hat{y}_i 's are ORTHOGONAL \Rightarrow use \hat{y}_i 's for storage.

EXAMPLE:

$$y_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \quad y_2 = \begin{pmatrix} -1 \\ -1 \\ 1 \\ 1 \end{pmatrix} \quad y_3 = \begin{pmatrix} -1 \\ 1 \\ -1 \\ 1 \end{pmatrix}$$

$$W = \frac{1}{4} (y_1 y_1^T + y_2 y_2^T + y_3 y_3^T) - \frac{3}{4} I = \frac{1}{4} \begin{pmatrix} 0 & 1 & 1 & -1 \\ 1 & 0 & -1 & 1 \\ 1 & -1 & 0 & 1 \\ -1 & 1 & 1 & 0 \end{pmatrix}$$

$$W y_1 = \frac{1}{4} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} = \frac{1}{4} y_1, \quad W y_2 = \frac{1}{4} y_2, \quad W y_3 = \frac{1}{4} y_3.$$

$$E = -\frac{1}{2} \sigma^T W \sigma \Rightarrow \boxed{-\frac{1}{2} = \frac{p-n}{2} \leq E \leq \frac{p}{n} = \frac{3}{2}}$$

Let $y = \begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \end{pmatrix}$ be given. (y is "close" to y_1)

$$E(y) = -\frac{1}{2} y^T W y = -\frac{1}{2} (1 \ 1 \ 1 \ -1) \begin{pmatrix} 3 \\ -1 \\ -1 \\ 1 \end{pmatrix} = 0$$

Synchronous update:

$$v(0) = W y = \frac{1}{4} \begin{pmatrix} 3 \\ -1 \\ -1 \\ 1 \end{pmatrix} \Rightarrow o(1) = \Gamma(v(0)) = \begin{pmatrix} 1 \\ -1 \\ -1 \\ 1 \end{pmatrix}$$

$$v(1) = W v(1) = \frac{1}{4} \begin{pmatrix} -3 \\ 3 \\ 3 \\ -3 \end{pmatrix} \Rightarrow o(2) = \Gamma(v(1)) = \begin{pmatrix} -1 \\ 1 \\ 1 \\ -1 \end{pmatrix}$$

$$\begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ -1 \\ -1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} -1 \\ 1 \\ 1 \\ -1 \end{pmatrix}$$

$E=0$ $E=0$ $E=0$

Asynchronous update:

$$\begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_1]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_2]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_3]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix}$$

$$\begin{matrix} \text{update} \\ \rightarrow \\ \text{o}_4 \end{matrix} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_1]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_2]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_3]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_4]{\text{update}} \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix}$$

End of cycle

End of cycle

RESULT: $\begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \rightarrow -y_3!$ (close to $y!$)

Cost: $E = -\frac{1}{2} y_3^T W y_3 = -\frac{1}{2}$ minimum

Change the order of update:

$$y = \begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[\text{o}_1]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_3]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_2]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_1]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

end of cycle

$$\begin{matrix} \text{update} \\ \rightarrow \\ \text{o}_4 \end{matrix} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_3]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_2]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[\text{o}_1]{\text{update}} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

end of cycle

RESULT: $\Rightarrow \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} = y_1!$

Cost: $E = -\frac{1}{2} y_1^T W y_1 = -\frac{1}{2}$: minimum.

* Generalization.

$$\left. \begin{aligned} v(k) &= w_0(k) - \theta \\ o(k+1) &= \Gamma(v(k)) \end{aligned} \right\} \Rightarrow \boxed{o(k+1) = \Gamma(w_0(k) - \theta)}$$

Given patterns $y_1, \dots, y_p \in \mathbb{R}^n$

For fixed point property (Problem 1)

Choose $\theta = 0$.

$$y_i = \Gamma(w y_i) \quad i = 1, 2, \dots, p.$$

$$A = [y_1 \ y_2 \ \dots \ y_p] \in \mathbb{R}^{n \times p} \quad (n \times p \text{ matrix})$$

$$\Rightarrow \boxed{A = \Gamma(WA)} \Leftrightarrow \boxed{WA = \Gamma^{-1}(A)}$$

$$\text{call } \boxed{P = \Gamma^{-1}(A)} \Rightarrow \boxed{WA = P}$$

properties of P :

i) row space of P is in the row space of A

$$\text{rank}(A) = \text{rank} \begin{pmatrix} A \\ P \end{pmatrix}$$

$$\text{ii) } \text{sgn}(a_{ij}) = \text{sgn}(p_{ij})$$

conversely, for any P satisfying i) and ii), we can find a suitable A .

Typical choices for P :

$$i) \quad P = DA \quad , \quad D = \begin{pmatrix} \alpha_1 & & 0 \\ & \ddots & \\ 0 & & \alpha_n \end{pmatrix} \quad \alpha_i > 0$$

$$ii) \quad \alpha_1 = \alpha_2 = \dots = \alpha_n = \tau_1 \Rightarrow P = \tau_1 A \quad , \quad \tau_1 > 0.$$

In general, let us use Singular Value Decomposition (SVD)

$$\text{rank}(A) = r < p \quad , \quad A \in \mathbb{R}^{n \times p}$$

$$A = U \Sigma V^T$$

U : orthogonal matrix $(U U^T = U^T U = I) \in \mathbb{R}^{n \times n}$

$$U = \left[\underbrace{U_1}_r \quad \underbrace{U_2}_{n-r} \right] \quad \left. \vphantom{\begin{matrix} U_1 \\ U_2 \end{matrix}} \right\} n \quad \begin{matrix} U_1: n \times r \\ U_2: n \times (n-r) \end{matrix}$$

V : orthogonal matrix $(V V^T = V^T V = I) \in \mathbb{R}^{p \times p}$

$$V = \left[\underbrace{V_1}_r \quad \underbrace{V_2}_{p-r} \right] \quad \left. \vphantom{\begin{matrix} V_1 \\ V_2 \end{matrix}} \right\} p \quad \begin{matrix} V_1: p \times r \\ V_2: p \times (p-r) \end{matrix}$$

$$\Sigma = \left(\begin{array}{cc} \Sigma_1 & 0 \\ \underbrace{0}_r & \underbrace{0}_{n-r} \end{array} \right) \quad \left. \vphantom{\begin{matrix} \Sigma_1 \\ 0 \\ 0 \end{matrix}} \right\} \begin{matrix} r \\ p-r \end{matrix} \quad \begin{matrix} \Sigma: n \times p \\ \Sigma_1: r \times r \end{matrix}$$

$$\Sigma_1 = \begin{pmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \ddots \\ & & & \sigma_r \end{pmatrix} \quad \sigma_1 > \sigma_2 > \dots > \sigma_r > 0$$

σ_i : singular values of A .

$$AA^T = U \Sigma V^T V \Sigma^T U^T = U \Sigma \Sigma^T U^T$$

$$= U \begin{pmatrix} \Sigma_1^2 & 0 \\ 0 & 0 \end{pmatrix} U^T$$

$$\Sigma_1^2 = \begin{pmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \dots & \\ & & & \sigma_r^2 \end{pmatrix}$$

$$\Rightarrow \boxed{\sigma_i = \sqrt{\begin{matrix} \text{nonzero} \\ \text{eigenvalue of } AA^T \end{matrix}} \quad i=1, 2, \dots, r}$$

$$A = U \Sigma V^T = (U_1 \ U_2) \begin{pmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} V_1^T \\ V_2^T \end{pmatrix}$$

$$\boxed{A = U_1 \Sigma_1 V_1^T}$$

$$\Rightarrow WA = P$$

$$\Rightarrow WA = W U_1 \Sigma_1 V_1^T = P$$

$$\Rightarrow W U_1 \Sigma_1 V_1^T V_1 = P V_1 \quad (V_1^T V_1 = I)$$

$$\Rightarrow W U_1 \Sigma_1 = P V_1$$

$$\Rightarrow \boxed{W U_1 = P V_1 \Sigma_1^{-1}}$$

$$\boxed{W U_2 = X}$$

X: $n \times (n-r)$ and ARBITRARY!

$$\Rightarrow W (U_1 \ U_2) = (P V_1 \Sigma_1^{-1} \ ; \ X)$$

$$W = (P V_1 Z_1^{-1} : X) \begin{pmatrix} U_1^T \\ U_2^T \end{pmatrix}$$

$$W = P V_1 Z_1^{-1} U_1^T + X U_2^T$$

Conclusion: For any P satisfying i), ii) and for any arbitrary X , this W solves the fixed point problem! (solves problem 1).

IDEA: Manipulate P and X to satisfy problems 2-4.

A special choice:

$$P = \tau_1 A, \quad X = -\tau_2 U_2 \quad \tau_1 > 0, \tau_2 > 0$$

$$\begin{aligned} \Rightarrow W &= \tau_1 A \cdot V_1 Z_1^{-1} U_1^T - \tau_2 U_2 U_2^T \\ &= \tau_1 U_1 \Sigma_1 V_1^T V_1 Z_1^{-1} U_1^T - \tau_2 U_2 U_2^T \\ &= \tau_1 U_1 \Sigma_1 Z_1^{-1} U_1^T - \tau_2 U_2 U_2^T \end{aligned}$$

$$W = \tau_1 U_1 U_1^T - \tau_2 U_2 U_2^T$$

3) $W = W^T$

by choosing τ_1 and τ_2 appropriately, we may have $W = 0$! (problem 4).

Minimum:

$$*) \quad U = [u_1 \quad u_2] \quad U^T U = I$$

$$\Rightarrow \begin{bmatrix} u_1^T \\ u_2^T \end{bmatrix} [u_1 \quad u_2] = \begin{bmatrix} u_1^T u_1 & u_1^T u_2 \\ u_2^T u_1 & u_2^T u_2 \end{bmatrix}$$

$$\Rightarrow u_1^T u_1 = I, \quad u_2^T u_2 = I, \quad u_1^T u_2 = 0 \quad u_2^T u_1 = 0.$$

$$*) \quad U U^T = I \Rightarrow (u_1 \quad u_2) \begin{pmatrix} u_1^T \\ u_2^T \end{pmatrix} = u_1 u_1^T + u_2 u_2^T = I$$

$$*) \quad A = U_1 \Sigma_1 U_1^T \quad \hookrightarrow \quad A = [y_1 \quad \dots \quad y_r]$$

\Rightarrow y_i are in the column space of U_1 , and hence are orthogonal to U_2 .

$$* \quad y_i^T (u_1 u_1^T + u_2 u_2^T) y_i = y_i^T y_i$$

$$\Rightarrow y_i^T u_1 u_1^T y_i = y_i^T y_i = \|y_i\|^2 = n \quad (\text{binary case!})$$

$$* \quad \boxed{W = \tau_1 u_1 u_1^T - \tau_2 u_2 u_2^T}$$

$$\Rightarrow \begin{aligned} \lambda_1 = \lambda_2 = \dots = \lambda_r = \tau_1 & \quad (r \text{ eigenvalues are } \tau_1) \\ \lambda_{r+1} = \dots = \lambda_n = -\tau_2 & \quad (\text{remaining ones are } -\tau_2) \end{aligned}$$

$$\Rightarrow \lambda_{\min}(W) \|y\|^2 \leq y^T W y \leq \lambda_{\max}(W) \|y\|^2$$

$$\Rightarrow -\frac{\lambda_{\max}(W)}{2} \|y\|^2 \leq -\frac{1}{2} y^T W y \leq -\frac{\lambda_{\min}(W)}{2} \|y\|^2$$

$$\left. \begin{aligned} \lambda_{\max}(W) &= \tau_1 \\ \lambda_{\min}(W) &= -\tau_2 \\ \|y\|^2 &= n \end{aligned} \right\} \Rightarrow$$

$$\boxed{-\frac{\tau_1 n}{2} \leq -\frac{1}{2} y^T W y \leq \frac{\tau_2 n}{2}}$$

$$\begin{aligned}
 E(y_i) &= -\frac{1}{2} y_i^T W y_i = -\frac{1}{2} y_i^T (\tau_1 u_1 u_1^T - \tau_2 u_2 u_2^T) y_i \\
 &= -\frac{\tau_1}{2} y_i^T u_1 u_1^T y_i + \frac{\tau_2}{2} y_i^T u_2 u_2^T y_i \\
 &= -\frac{\tau_1}{2} \|y_i\|^2 = -\frac{\tau_1 \eta}{2}.
 \end{aligned}$$

Conclusion: y_i 's become minima of cost!
solves problem 4!

Relation with outer product rule.

$$W = \frac{1}{n} \sum_{i=1}^p y_i y_i^T - \frac{p}{n} I$$

Assume that y_i 's are ORTHOGONAL.

$$A = [y_1 \ y_2 \ \dots \ y_p]$$

$$\|y_i\| = \sqrt{(y_i)_1^2 + \dots + (y_i)_n^2} = \sqrt{n}$$

$$A = \underbrace{\begin{bmatrix} \frac{y_1}{\sqrt{n}} & \frac{y_2}{\sqrt{n}} & \dots & \frac{y_p}{\sqrt{n}} \end{bmatrix}}_{U_1} \underbrace{\begin{bmatrix} \sqrt{n} & & 0 \\ & \dots & \\ 0 & & \sqrt{n} \end{bmatrix}}_{\Sigma_1} \underbrace{I}_{V_1^T}$$

$$\Rightarrow \boxed{U_1 = \frac{1}{\sqrt{n}} A}$$

$$\boxed{U_1 U_1^T + U_2 U_2^T = I}$$

$$W = \frac{1}{n} \sum_{i=1}^p y_i y_i^T - \frac{p}{n} I = \frac{1}{n} A A^T - \frac{p}{n} I$$

$$= \frac{1}{n} A \cdot \frac{1}{n} A^T - \frac{p}{n} I$$

$$= u_1 u_1^T - \frac{p}{n} (u_1 u_1^T + u_2 u_2^T)$$

$$= (1 - \frac{p}{n}) u_1 u_1^T - \frac{p}{n} u_2 u_2^T$$

$$= \tau_1 u_1 u_1^T - \tau_2 u_2 u_2^T$$

Same as outer product rule with $\tau_1 = 1 - \frac{p}{n}$, $\tau_2 = -\frac{p}{n}$

What if the patterns are not orthogonal?

Can we still use outer-product rule?

A Trick: Dummy augmentation:

$$y_i = \begin{pmatrix} y_{i1} \\ y_{in} \end{pmatrix} \quad y_j = \begin{pmatrix} y_{j1} \\ y_{jn} \end{pmatrix}$$

⇒ add dummy entries.

$$\hat{y}_i = \begin{pmatrix} y_{i1} \\ y_{in} \\ \text{dummy} \\ y_{im} \end{pmatrix} \quad \hat{y}_j = \begin{pmatrix} y_{j1} \\ y_{jn} \\ \text{dummy} \\ y_{jm} \end{pmatrix}$$

← Dummy entries →

such that $\hat{y}_i \perp \hat{y}_j$.

What happens if the patterns are not orthogonal?

$$W = \frac{1}{n} AA^T - \frac{p}{n} I$$

$$WA = \frac{1}{n} AAA^T - \frac{p}{n} A = P$$

$$\Rightarrow P = \left(\frac{1}{n} AA^T - \frac{p}{n} I \right) A$$

\Rightarrow row space of P is in row space of A

$$\text{sign}(P_{ij}) = \text{sign}(a_{ij}) ?$$

$$A = [y_1 \ y_2 \ \dots \ y_p]$$

$$A^T A = \begin{bmatrix} y_1^T y_1 & y_1^T y_2 & \dots & y_1^T y_p \\ \vdots & \vdots & \ddots & \vdots \\ y_p^T y_1 & \dots & \dots & y_p^T y_p \end{bmatrix}$$

$$y_i^T y_i = \|y_i\|^2 = n \quad y_i^T y_j = ?$$

$$(y_{i1} \ \dots \ y_{in}) \begin{pmatrix} y_{j1} \\ \vdots \\ y_{jn} \end{pmatrix} = y_{i1} y_{j1} + \dots + y_{in} y_{jn}$$

Assume that h_{ij} bits are different, and $n - h_{ij}$ bits are the same.

$$y_i^T y_j = n - h_{ij} - h_{ij} = n - 2h_{ij}$$

h_{ij} : Hamming distance between y_i and y_j .

$$P = \frac{1}{n} A A^T A - \frac{p}{n} A = \frac{1}{n} A (A^T A - I)$$

$$\begin{bmatrix} p_{11} & \dots & p_{1n} \\ & & p_{ij} \\ & & \dots \end{bmatrix} = \frac{1}{n} \begin{bmatrix} a_{11} & \dots & a_{1n} \\ & & a_{ij} \\ & & \dots \end{bmatrix} \begin{bmatrix} n-p & & & n-2h_{1p} \\ & n-p & & \\ & & \dots & \\ & & & n-p \end{bmatrix}$$

\Rightarrow $\text{sign}(a_{ij}) = \text{sign}(p_{ij})$ is guaranteed if we have:

$$\boxed{\sum_{\substack{i=1 \\ i \neq j}}^p |n-2h_{ij}| < n-p}$$

\Leftrightarrow the matrix $AA^T - pI$ is **DIAGONALLY DOMINANT!**

$$p_{ij} = a_{i1}(n-2h_{1j}) + a_{i2}(n-2h_{2j}) + \dots + a_{ij}(n-p) + \dots$$

$$a_{ij} = +1 \rightarrow p_{ij} = (n-p) + \sum_{\substack{k=1 \\ k \neq j}}^p a_{ik}(n-2h_{kj}) \geq (n-p) - \sum_{\substack{k=1 \\ k \neq j}}^p |n-2h_{kj}| > 0$$

$$a_{ij} = -1 \rightarrow p_{ij} = -(n-p) + \sum_{\substack{k=1 \\ k \neq j}}^p a_{ik}(n-2h_{kj}) \leq -(n-p) + \sum_{\substack{k=1 \\ k \neq j}}^p |n-2h_{kj}| < 0$$

hence in both cases $\text{sign}(a_{ij}) = \text{sign}(p_{ij})$