8.3 Householder变换与矩阵的正交分解

一、初等反射阵(Householder变换阵)

定义 设非零向量 $W \in \mathbb{R}^n, W = (w_1, w_2, \dots, w_n)^T,$ 且满足条件 $\|W\|_2 = 1$,形如

$$\boldsymbol{H} = \boldsymbol{I} - 2\boldsymbol{W}\boldsymbol{W}^T$$

的n阶方阵称为初等反射阵,或称为Householder

交換阵.
$$1-2w_1^2$$
 $-2w_1w_2$ \cdots $-2w_1w_n$ $H =$ $-2w_2w_1$ $1-2w_2^2$ \cdots $-2w_2w_n$ \cdots \cdots \cdots \cdots $-2w_nw_1$ $-2w_nw_2$ \cdots $1-2w_n^2$

例:
$$W = \left(\frac{1}{\sqrt{2}} \quad 0 \quad \frac{1}{\sqrt{2}}\right)^T \in \mathbb{R}^3, ||W||_2 = 1$$

$$H = I - 2WW^{T} = I - 2 \begin{vmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ \frac{1}{\sqrt{2}} \end{vmatrix} \begin{pmatrix} \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{pmatrix}$$

$$= \begin{bmatrix} 0 & 0 & -1 \\ 0 & 1 & 0 \\ -1 & 0 & 0 \end{bmatrix}$$

H阵的性质:

(1) 非奇异
$$\det(H) = 1 - 2W^T W = -1$$

(2) 对称正交

$$H = H^{T}$$

$$HH^{T} = H^{2} = (I - 2WW^{T})(I - 2WW^{T})$$

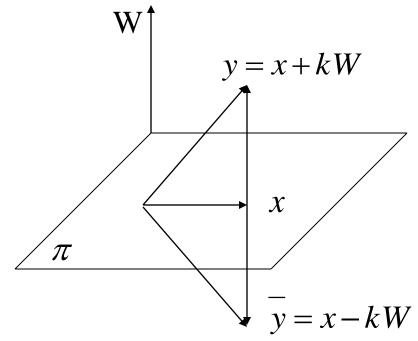
$$= I - 4WW^{T} + 4WW^{T}WW^{T} = I$$

$$H = \begin{bmatrix} 1 - 2w_1^2 & -2w_1w_2 & \cdots & -2w_1w_n \\ -2w_2w_1 & 1 - 2w_2^2 & \cdots & -2w_2w_n \\ \cdots & \cdots & \cdots & \cdots \\ -2w_nw_1 & -2w_nw_2 & \cdots & 1 - 2w_n^2 \end{bmatrix}$$

(3) 镜映射-几何意义

平面 π 方程 $W^T x = 0 \quad \forall x \in \pi$ 若 $x \in \pi$, $Hx = (I - 2WW^T)x = x - 2WW^T x = x$

若 $y \notin \pi$, $Hy = H(x+kW) = x+k(I-2WW^T)W$ = $x+kW-2kWW^TW = x-kW = y$

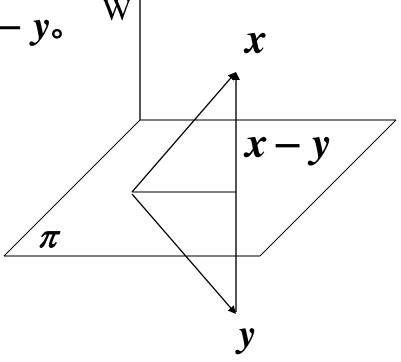


H阵的作用:

定理 设两个不相等的n维向量 $x, y \in \mathbb{R}^n, x \neq y$,但 $\|x\|_2 = \|y\|_2$,则存在householder阵

$$H = I - 2\frac{UU^T}{\|U\|_2^2}$$

使Hx = y, 其中U = x - y。



证: 若设W =
$$\frac{U}{\|U\|_2}$$
, 则有 $\|W\|_2 = 1$, 因此
$$H = I - 2WW^T = I - 2\frac{UU^T}{\|U\|_2^2}$$

$$= I - 2\frac{(x - y)}{\|x - y\|_2^2}(x^T - y^T)$$

$$Hx = x - 2\frac{(x - y)}{\|x - y\|_2^2}(x^T - y^T)x$$

$$= x - 2\frac{(x - y)(x^Tx - y^Tx)}{\|x - y\|_2^2}$$
因为 $\|x - y\|_2^2 = (x^T - y^T)(x - y) = 2(x^Tx - y^Tx)$

因为
$$\|x-y\|_2^2 = (x^T - y^T)(x - y) = 2(x^T x - y^T x)$$

代入上式后即得到x = y : $x^T x = y^T y$,

$$x^T x = y^T y,$$

$$x^T y = y^T x$$

1. *Householder*变换可以将给定的向量变为一个与任一个 $e_i \in R^n (i = 1, 2, \dots, n)$ 同方向的向量。

即: $\forall x = (x_1, x_2, \dots, x_n)^T \in \mathbb{R}^n, x \neq 0$, 可构造H阵, 使 $Hx = y = -\sigma_i e_i = (0, ..., 0, -\sigma_i, 0, \cdots, 0)^T \in \mathbb{R}^n$ 其中 $\sigma_i = sign(x_i) ||x||_2 = sign(x_i) (\sum_{i=1}^n x_k^2)^{\frac{1}{2}},$ $sign(x_i) = \begin{cases} 1 & x_i \ge 0 \\ -1 & x_i < 0 \end{cases}$

 $U = x - y = x + \sigma_i e_i = (x_1, \dots, x_i + \sigma_i, \dots, x_n)^T,$

构造初等反射阵

$$H = I - 2WW^{T} = I - 2\frac{UU^{T}}{\|U\|^{2}} = I - \frac{1}{\rho}UU^{T}$$

有 $Hx = y = -\sigma_i e_i$

其中

$$\rho = \frac{1}{2}U^{T}U = \frac{1}{2}(x_{1}^{2} + ... + (x_{i} + \sigma_{i})^{2} + ... + x_{n}^{2})$$

$$= \frac{1}{2}(2x_{i}\sigma_{i} + 2\sigma_{i}^{2}) = \sigma_{i}(x_{i} + \sigma_{i})$$

例 已知向量 $x = (2,0,2,1)^T$,试构造Householder阵,使 $Hx = Ke_3$,其中 $e_3 = (0,0,1,0)^T \in R^4$, $K \in R$ 。

解:
$$\sigma_3 = sign(x_3) \|x\|_2 = \sqrt{4+0+4+1} = 3$$
, 因 $x_3 = 2 > 0$,

故取
$$K = -\sigma_3 = -3$$
 于是 $y = -\sigma_3 e_3 = Ke_3 = (0, 0, -3, 0)^T$,

$$U = x - y = (2,0,5,1)^{T}, \rho = \sigma_3(\sigma_3 + x_3) = 3(3+2) = 15$$

$$H = I - \frac{1}{\rho} UU^{T} = \frac{1}{15} \begin{bmatrix} 11 & 0 & -10 & -2 \\ 0 & 1 & 0 & 0 \\ -10 & 0 & -10 & -5 \\ -2 & 0 & -5 & 14 \end{bmatrix}$$

2. 构造*H*阵,将向量 $x = (x_1, \dots, x_k, x_{k+1}, \dots, x_n)^T$ 的后面n - k个分量约化为零 $(1 \le k < n)$ 。

即: 任给定 $x = (x_1, x_2, \dots, x_n)^T \neq 0$,构造 $H_k \in \mathbb{R}^{n \times n}$,使 $H_k x = (x_1, x_2, \dots, x_{k-1}, -\sigma_k, 0, \dots, 0)^T$

推导: $\forall x = (x_1, x_2, \dots, x_n)^T \neq \mathbf{0}$

$$y = (x_1, \dots, x_{k-1}, -\sigma_k, 0, \dots, 0)^T$$

$$\sigma_k = sign(x_k)(\sum_{i=k}^n x_i^2)^{\frac{1}{2}}, \quad sign(x_k) = \begin{cases} 1 & x_k \ge 0 \\ -1 & x_k < 0 \end{cases}$$

$$U^{(k)} = x - y = (0, \dots, 0, x_k + \sigma_k, x_{k+1}, \dots, x_n)^T$$

$$H_k = I - \frac{1}{\rho_k} U^{(k)} (U^{(k)})^T$$
其中 $\rho_k = \frac{1}{2} U^{(k)T} U^{(k)} = \sigma_k (\sigma_k + x_k)$
特别,取k = 1.
$$\forall x = (x_1, x_2, \dots, x_n)^T \in R^n, x \neq 0, \text{可构造H阵},$$
使 $Hx = y = -\sigma_1 e_1 = (-\sigma_1, 0, \dots, 0)^T \in R^n$
其中 $\sigma_1 = sign(x_1) \|x\|_2 = sign(x_1) (\sum_{i=1}^n x_i^2)^{\frac{1}{2}},$

$$sign(x_1) = \begin{cases} 1 & x_1 \geq 0 \\ -1 & x_1 < 0 \end{cases}$$

$$U^{(1)} = x + \sigma_1 e_1 = (\sigma_1 + x_1, x_2, \dots, x_n)^T,$$

可构造初等反射阵

$$H_1 = I - 2WW^T = I - 2\frac{U_1U_1^T}{\left\|U_1\right\|^2} = I - \frac{1}{\rho}U_1U_1^T$$

有
$$H_1 x = y = -\sigma_1 e_1$$

其中 $\rho_1 = \frac{1}{2} U_1^T U_1 = \frac{1}{2} ((x_1 + \sigma_1)^2 + x_2^2 + \dots + x_n^2)$
 $= \frac{1}{2} (2x_1 \sigma_1 + 2\sigma_1^2) = \sigma_1 (x_1 + \sigma_1)$

例:已知向量 $x = (2,2,1)^T$,试构造初等反射阵使y = Hx最后一个元素为零。

解
$$k = 2$$
,构造 H_2

$$\sigma_2 = sign(x_2)(x_2^2 + x_3^2)^{\frac{1}{2}} = \sqrt{5}$$

$$U^{(2)} = (0, \sigma_2 + x_2, x_3)^T = (0, 2 + \sqrt{5}, 1)^T$$

$$\rho_2 = \sigma_2(x_2 + \sigma_2) = 5 + 2\sqrt{5}$$
于是 $H_2x = (x_1, -\sigma_2, 0)^T = (2, -\sqrt{5}, 0)^T$
计算 H_2 , $H_2 = I - \frac{1}{\rho_2}U^{(2)}(U^{(2)})^T$

$$H_{2} = \frac{1}{5+2\sqrt{5}} \begin{bmatrix} 5+2\sqrt{5} & 0 & 0\\ 0 & -(4+2\sqrt{5}) & -(2+\sqrt{5})\\ 0 & -(2+\sqrt{5}) & (4+2\sqrt{5}) \end{bmatrix}$$

$$H_2 x = (x_1, -\sigma_2, 0)^T = (2, -\sqrt{5}, 0)^T$$

二、矩阵的正交分解

1、正交分解的基本定理

定理 $\forall A \in R^{m \times n}$ 是列满秩矩阵 (m > n, r(A) = n),存在分解式A = QR,其中 $Q \in R^{m \times n}$ 列法正交矩阵, $R \in R^{n \times n}$ 非奇异上三角阵。若限定R阵对角元符号,则分解式是唯一的。

当m = n时, $Q \in R^{n \times n}$ 正交阵, $R \in R^{n \times n}$ 非奇异上三角阵。

$$A_{n imes n} = QR = egin{bmatrix} * & \dots & * \ dots & \ddots & dots \ * & \dots & * \ \end{bmatrix} egin{bmatrix} * & \dots & * \ 0 & \ddots & dots \ \end{bmatrix}$$

$$A_{m imes n} = QR = egin{bmatrix} * & \dots & * \ \vdots & \ddots & \vdots \ * & \dots & * \end{bmatrix}_{m imes n} egin{bmatrix} * & \dots & * \ 0 & \ddots & \vdots \ 0 & \ddots & \vdots \ \end{pmatrix}_{n imes n}$$

$$A_{m imes n} = QR = egin{bmatrix} * & \cdots & * \ : & \ddots & : \ * & \cdots & * \end{bmatrix}_{m imes m} egin{bmatrix} * & \cdots & * \ 0 & & * \ 0 & \cdots & 0 \end{bmatrix}_{m imes m}$$

称形如

$$H = egin{bmatrix} h_{11} & h_{12} & \cdots & h_{1n-1} & h_{1n} \ h_{21} & h_{22} & \cdots & h_{2n-1} & h_{2n} \ h_{32} & h_{33} & \cdots & h_{3n} \ & \ddots & \ddots & dots \ h_{nn-1} & h_{nn} \end{bmatrix}$$

的矩阵为上海森堡(Hessenberg)阵。如果此对角线元 h_{ii-1} ($i=2,3,\dots,n$)全不为零,则称该矩阵为不可约的上Hessenberg矩阵。

讨论用 Householder 变换将一般矩阵A相似变换成Hessenberg阵

例:用豪斯霍尔德方法将

$$\mathbf{A} = \mathbf{A}_1 = \begin{bmatrix} -4 & -3 & -7 \\ 2 & 3 & 2 \\ 4 & 2 & 7 \end{bmatrix}$$

矩阵约化为上Hessenberg阵。

解:选取初等反射阵R1使

$$R_1c_1 = -\sigma_1e_1, \sharp + c_1 = (2,4)^T$$

(1) 计算
$$\mathbf{R}_1$$
: $\alpha = \max(2,4) = 4, \mathbf{c}_1 \to \mathbf{c}_1' = (0.5,1)^T$

$$\begin{cases} \boldsymbol{\sigma} = \sqrt{1.25} = 1.118034, \\ \boldsymbol{u}_1 = \boldsymbol{c}_1' + \boldsymbol{\sigma} \boldsymbol{e}_1 = (1.618034, 1)^T, \\ \boldsymbol{\beta}_1 = \boldsymbol{\sigma}(\boldsymbol{\sigma} + 0.5) = 1.809017, \\ \boldsymbol{\sigma}_1 = \boldsymbol{\alpha} \boldsymbol{\sigma} = 4.472136, \\ \boldsymbol{R}_1 = \boldsymbol{I} - \boldsymbol{\beta}_1^{-1} \boldsymbol{u}_1 \boldsymbol{u}_1^T. \end{cases}$$

则有

$$\mathbf{R}_1 \mathbf{c}_1 = -\boldsymbol{\sigma}_1 \mathbf{e}_1.$$

(2) 约化计算:

$$\boldsymbol{U}_1 = \begin{bmatrix} 1 & 0 \\ 0 & \boldsymbol{R}_1 \end{bmatrix}$$

则
$$\boldsymbol{A}_2 = \boldsymbol{U}_1 \boldsymbol{A} \boldsymbol{U}_1$$

$$\begin{bmatrix} -4 & 7.602631 & -0.447214 \\ -4.472136 & 7.799999 & -0.400000 \\ 0 & -0.399999 & 2.2000000 \end{bmatrix}$$

$$=H$$