数学中的问题介绍

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Pb 1. Noticed that

$$||y - As||_2 = ||Es||_2$$

 $\leq ||E||_2| \cdot |s||_2$

Then

$$||E||_2 \ge \frac{||y - As||_2}{||s||_2}$$

Then we try to compute $||E^*||_2$.

$$\begin{split} ||s^T s \cdot E^*||_2^2 &= ||(y - As)s^T||_2^2 \\ &= \max_{|x| = 1} |x^T s (y - As)^T (y - As)s^T x| \\ &= |y - As|_2^2 \cdot \max_{|x| = 1} |x^T s s^T x| \\ &= |y - As|_2^2 \cdot \max_{|x| = 1} |x^T s|^2 \\ &= |y - As|_2^2 \cdot |s|_2^2 \end{split}$$

The final equation is inferred from the Cauchy-Schwarz inequality.

Thus,

$$||E^*||_2 = \frac{||y - As||_2}{||s||_2}$$

Noticed that

$$E^* \cdot s = \frac{(y - As)s^T s}{s^T s} = y - As$$

Therefore, E^* is a solution of the question.

Pb 2. For |x| = 1, $y = A^{-1}x$.

Then Ay = x with norm 1.

$$\Rightarrow \left| \sum_{j=1}^{n} a_{ij} y_j \right| \le 1 \ \forall 1 \le j \le n.$$

If $|y_i| = \max |y_1|, \cdots, |y_n|$, then we have

$$1 \ge \sum_{j=1}^{n} |a_{ij}y_j| \ge |a_{ii}y_i| - \sum_{j \ne i} |y_i| \cdot |a_{ij}|$$

 \Rightarrow

$$|y|_{\infty} = |y_i| \le \frac{1}{|a_{ii}| - \sum_{j \ne i} |a_{ij}|}$$

Therefore

$$|A^{-1}x| =_{\infty} |y|_{\infty} \le \max_{1 \le i \le n} \frac{1}{|a_{ii}| - \sum_{i \ne i} |a_{ij}|} = (\min_{1 \le i \le n} |a_{ii}| - \sum_{j \ne i} |a_{ij}|)^{-1}$$

So

$$||A^{-1}||_{\infty} \le (\min_{1 \le i \le n} |a_{ii}| - \sum_{j \ne i} |a_{ij}|)^{-1}$$

Pb 3. $||L||_2^2 = |\rho(L^T L)|$.

$$||A||_2^2 = |\rho(A^T A)| = |\rho(A^2)| = |\rho(A)|^2 = |\rho(LL^T)| = ||L^T||_2^2$$

Noticed that if $L^T L \vec{x} = \lambda \vec{x}$, then $L L^T (L \vec{x}) = \lambda L \vec{x}$. The converse is also true. Hence,

$$\rho(L^T L) = \rho(L L^T)$$

Therefore, $||L||_2^2 = ||L^T||_2^2 = ||A||_2^2$.

Pb 4. Since by the definition, for each step k, the matrix should be like:

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1k} & \cdots & a_{1n} \\ a_{22} & \cdots & a_{2k} & \cdots & a_{2n} \\ & \ddots & \vdots & \vdots & \vdots \\ & & & a_{kk} & \cdots & a_{kn} \\ & & \vdots & \ddots & \vdots \\ & & & & a_{nk} & \cdots & a_{nn} \end{pmatrix}$$

where me will make sure that $|a_{kk} = \max_{i \geq k} \{|a_{ik}|, |a_{ki}|\}.$

Since the following steps do not change the k^{th} row, so the obtained upper triangular matrix U satisfies the condition:

$$u_{ii} = \max_{i \ge k} |u_{ik}|$$

Pb 5. Let $e_i = (0, 0, \dots, 1, \dots, 0)$ with 1 in the i^{th} term.

Now $Ae_i = a_i$ and $||e_i||_p \le 1$.

So $||A||_p \ge ||a_i||_p$.

Let
$$x = \frac{Ae_i}{||a_i||_p}$$
, then $||x||_p = 1$, $A^{-1}x = \frac{e_i}{||a_i||_p}$.

$$\Rightarrow ||A^{-1}||_p \ge \frac{1}{||a_i||_p}.$$

So

$$||A||_p \cdot ||A^{-1}||_p \ge \frac{||a_i||_p}{||a_i||_p}$$

Pb 6. For n = 1, let L = I, D = A, then $A = LDL^T$ satisfies the condition.

If n-1 there exists the representation, the for n, denote

$$A = \begin{pmatrix} A' & b \\ b^T & c \end{pmatrix}$$

Let $A' = L'D'L'^T$, where L' lower triangular matrix and D' diagonal matrix.

Then let $y = (L'D')^{-1}b$

$$A = \begin{pmatrix} L' \\ y^T & 1 \end{pmatrix} \cdot \begin{pmatrix} D' & 0 \\ 0 & c - yD'y^T \end{pmatrix} \cdot \begin{pmatrix} L'^T & y \\ & 1 \end{pmatrix}$$

So A can be represented by LDL^{T} .

Pb 7. The above problem actually gives a possible coomputation method.

Let
$$L_1 = I_1$$
, $D_1 = [a_{11}]$.

We obtain L_i, D_i by the equation

$$L_i = \begin{pmatrix} L_{i-1} \\ y_i^T & 1 \end{pmatrix}$$

$$D_i = \begin{pmatrix} D_{i-1} & 0 \\ 0 & a_{ii} - y_i D_{i-1} y_i^T \end{pmatrix}$$

where $b = (a_{1i}, a_{2i}, \dots, a_{ni})^T$, $y = (L_{i-1}D_{i-1})^{-1}b$

Pb 8. 代码附件在压缩包中;

以下报告顺序按 1、高斯消元法; 2、高斯选主元消元法; 3、平方根法进行,分别对应 $Gauss.m, Gauss_choose.m, Cholesky.m$

通过时间测试 (sys1.m, sys2.m),第一题、第二题三种方法平均用时时间从小到大为 1, 2, 3。原因应该是 1 循环计算数最少,而 2 相比于 1 多了选主元的循环。3 则在解出 LU 分解的基础上又调用了一遍高斯算法,故时间最长。

在误差测试中,第一题三者没有明显区别,平方根法输出上略大,但三者相对误差量级均在e-16,可忽略不计;

而第二题三者相对误差均超过 400, 第三题偏低。从数据表现上看,前两种方法仅四项在 1 附近,而第三种方法为 6 项,说明第三种方法精度比前两者更好。

误差的精度差距是由于计算顺序决定的,第三种方法多乘法和减法,除法较少,因此解决各项接近的 Hilbert 矩阵更有优势。

数据附件 data.docx 在压缩包中;