Problem 0: Homework checklist

 $\checkmark \mathrm{I}$ didn't talk with any one about this homework.

 \checkmark Source-code are included at the end of this document.

Problem 1: The Cholesky Factorization

1. Here is my implementation of Cholesky decomposition in Matlab:

```
function L = cholesky(A)
n = size(A);
3 n = n(1);
4 L = zeros(n,n);
  L(1,1) = sqrt(A(1,1));
  for i=(1:n)
       sum1 = 0;
       for j=(1:i)
10
           if i==j
               L(j,j) = sqrt(A(j,j)-sum1);
               sum2 = 0;
               for k = (1:j-1)
                   sum2 = sum2 + L(i,k)*L(j,k);
15
16
17
               L(i,j) = 1/L(j,j) * (A(i,j)-sum2);
           end
19
           sum1 = sum1 + L(i,j)^2;
20
21
       end
   end
22
   end
```

2. Cholesky factorization is unique if A is positive definite and the decomposition need not be unique when A is positive semidefinite. Proof:

Get the LU decomposition of A = LU, and $u_{11} > 0, u_{22} > 0, ..., u_{mm} > 0$

Since $u_{11} > 0, ..., u_{mm} > 0$, we can get $T = \mathbf{D}^2$, where

$$\mathbf{D} = \begin{bmatrix} \sqrt{u_{11}} & 0 & \dots & 0 \\ 0 & \sqrt{u_{22}} & \dots & 0 \\ 0 & 0 & \dots & \dots \\ 0 & 0 & \dots & \sqrt{u_{mm}} \end{bmatrix}$$

$$\mathbf{\Delta} - \mathbf{L}\mathbf{U} - \mathbf{L}\mathbf{D}_0 \mathbf{W}$$

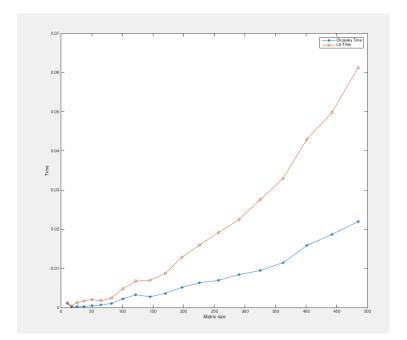


Figure 1: Performance comparison between LU decomposition and Cholesky factorization

Because $A_* = A$ and the LU factorization is unique, then $L = W^*$. Therefore the Cholesky factorization is unique if A is positive definite. Reference: http://math.utoledo.edu/mtsui/4350sp08/homework/Lec23.pdf

3. I computed the norm of difference of my Cholesky result and Matlab chlo:

$$1.9110e - 13$$

- 4. For each size of the matrices I repeated 10 times. The comparison result is shown. Obviously the the Cholesky factorization has better performance as the growth of matrix size.
- 5. Since ${\bf A}$ is positive definite, and assume an vector ${\bf v} = \begin{bmatrix} x_0 \\ {\bf x} \end{bmatrix}$, then

$$\mathbf{v}_T \mathbf{A} \mathbf{v} > 0$$

$$\begin{bmatrix} x_0 & \mathbf{x} \end{bmatrix} \begin{bmatrix} \alpha & \mathbf{b}_T \\ \mathbf{b} & \mathbf{C} \end{bmatrix} \begin{bmatrix} x_0 \\ \mathbf{x} \end{bmatrix} = \alpha x_0^2 + x_0 (\mathbf{x}^T \mathbf{b} + \mathbf{b}^T \mathbf{x}) + \mathbf{x}^T \mathbf{C} \mathbf{x} > 0$$

Then

$$\mathbf{x}^{T}(C - \frac{\mathbf{b}\mathbf{b}^{T}}{\alpha})\mathbf{x} = \mathbf{x}^{T}C\mathbf{x} - \frac{\mathbf{x}_{T}\mathbf{b}\mathbf{b}^{T}\mathbf{x}}{\alpha}$$

$$> -\alpha x_{0}^{2} - x_{0}(\mathbf{x}^{T}\mathbf{b} + \mathbf{b}^{T}\mathbf{x}) - \frac{\mathbf{x}^{T}\mathbf{b}\mathbf{b}^{T}\mathbf{x}}{\alpha}$$

$$= -\frac{1}{\alpha}\left[x_{0}^{2} + \frac{\mathbf{x}^{T}\mathbf{b} + \mathbf{b}^{T}\mathbf{x})x_{0}}{\alpha} + \frac{\mathbf{x}^{T}\mathbf{b}\mathbf{b}^{T}\mathbf{x}}{\alpha^{2}}\right]$$

$$= -\frac{1}{\alpha}\left(x_{0} + \frac{\mathbf{x}^{T}\mathbf{b}}{\alpha}\right)\left(x_{0} + \frac{\mathbf{b}^{T}\mathbf{x}}{\alpha}\right)$$

$$= -\frac{1}{\alpha}\left\|x_{0} + \frac{\mathbf{b}^{T}\mathbf{x}}{\alpha}\right\|^{2}$$

Because $\mathbf{x}^T (C - \frac{\mathbf{b}\mathbf{b}^T}{\alpha})\mathbf{x} > -\frac{1}{\alpha} \left\| x_0 + \frac{\mathbf{b}^T \mathbf{x}}{\alpha} \right\|^2$ holds for any vector \mathbf{x} . Therefore

$$\mathbf{x}^{T}(\mathbf{C} - \frac{\mathbf{bb}^{T}}{\alpha})\mathbf{x} > 0 \tag{1}$$

So $C - \frac{\mathbf{b}\mathbf{b}^T}{\alpha}$ is positive definite.

- 6. The base case is that C is a 1×1 .
- 7. In the Matlab code, we need check positiveness before take square root. The modified code is here:

```
function L = cholesky(A)
   n = size(A);
  n = n(1);
  L = zeros(n,n);
   L(1,1) = sqrt(A(1,1));
   for i=(1:n)
       sum1 = 0;
        for j=(1:i)
            if i==j
10
                if A(j,j)-sum1 \le 0
                    return % check whether A is positive ...
12
13
                    L(j,j) = sqrt(A(j,j)-sum1);
14
15
                end
            else
16
17
                for k = (1:j-1)
18
                    sum2 = sum2 + L(i,k)*L(j,k);
19
20
21
                L(i,j) = 1/L(j,j) * (A(i,j)-sum2);
            end
23
            sum1 = sum1 + L(i,j)^2;
24
25
        end
26
   end
27
   end
```

After testing, the matrix for Poisson's equation is not positive definite or negative definite.

Problem 2: Stability analysis

1.

$$V = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \frac{1}{n} x_i)^2$$
$$= \frac{1}{n-1} \left[\sum_{i=1}^{n} x_i^2 - \frac{1}{n} \left(\sum_{i=1}^{n} x_i \right)^2 \right]$$

The condition number is defined as:

$$\kappa = \lim_{\epsilon \to 0} \sup \left[\frac{|V(x) - V(x + \Delta x)|}{\epsilon V(x)} : ||\Delta x||_2 \le \epsilon ||x||_2 \right]$$

Then

$$\kappa = 2 \frac{\|x\|_2}{\sqrt{(n-1)V(x)}}$$

2. This is not appropriate. I will use q = 100 and s = 2 to do a test.

```
1  q = 500;
2  s = 7;
3  z = zeta(s);
4  h = z-sum((1:(q-1)).^(-s))
```

Hurwitz zeta function:

$$H(s,q) = \sum_{n=0}^{\infty} \frac{1}{(q+n)^s}$$
$$= \frac{1}{q^s} + \frac{1}{(q+1)^s} + \dots + \frac{1}{n^s}$$

Riemann zeta function:

$$\begin{split} R(s) &= \sum_{n=1}^{\infty} \frac{1}{n^s} \\ &= \frac{1}{1^s} + \frac{1}{2^s} + \ldots + \frac{1}{n^s} \\ &= \frac{1}{1^s} + \frac{1}{2^s} + \ldots + \frac{1}{(q-1)^2} + \frac{1}{q^s} + \frac{1}{(q+1)^s} + \ldots + \frac{1}{n^s} \\ &= \frac{1}{1^s} + \frac{1}{2^s} + \ldots + \frac{1}{(q-1)^2} + H(s,q) \end{split}$$

Output from Matlab is:

$$2.2204e - 15$$

But the true answer from Wolfram Alpha is

$$1.073081599928320\times 10^{-17}$$

Here is the explanation: when you calculate the Riemann zeta function, the terms with larger n will round off because they are relative smaller than terms with smaller n. The leading terms

$$\frac{1}{1^s} + \frac{1}{2^s} + \ldots + \frac{1}{(q-1)^2}$$

is dominant in R(s). But those are the terms we need for Hurwitz zeta with large q. Once you round off them, there would be large errors.

Problem 3: Backwards stability

$$fl(x_i) = x_i(1 + \epsilon_{ix})$$

$$fl(y_i) = y_i(1 + \epsilon_{iy})$$

where $|\epsilon_{ix}|, |\epsilon_{iy}| \leq \epsilon_{machine}$

$$\alpha = \mathbf{x}^T \mathbf{y}$$

$$= \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}$$

$$= \sum_{i=1}^n x_i y_i$$

Then

$$fl(\mathbf{x}^{T}\mathbf{y}) = \sum_{i=1}^{n} fl(x_{i}) \times fl(y_{i})$$

$$= [fl(x_{1}) \times fl(y_{1}) + fl(x_{2}) \times fl(y_{2}) + \dots + fl(x_{n}) \times fl(y_{n})] (1 + \epsilon_{addition})$$

$$= [x_{1}y_{1}(1 + \epsilon_{1x})(1 + \epsilon_{1y}) + \dots + x_{n}y_{n}(1 + \epsilon_{nx})(1 + \epsilon_{ny})] (1 + \epsilon_{addition})$$

$$= [x_{1}y_{1} + x_{2}y_{2} + \dots + x_{n}y_{n}] (1 + \epsilon_{1})(1 + \epsilon_{2})(1 + \epsilon_{3})$$

$$= [x_{1}y_{1} + x_{2}y_{2} + \dots + x_{n}y_{n}] (1 + O(\epsilon_{machine}))$$

Therefore the inner product is backwards stable.