

## Week 4-2: Examples using Cholesky decomposition

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April 21, 2022

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## Announcement

- Team members assigned

## Last time

- Pivoting
- Cholesky decomposition

## Today

- Examples using Cholesky

# 1 Examples using Cholesky decomposition

Notes about Cholesky:

Python NumPy and SciPy have two incompatible implementations of the Cholesky decomposition: `scipy.linalg.cholesky` and `numpy.linalg.cholesky`. NumPy version `numpy.linalg.cholesky` uses the definition used here while `scipy.linalg.cholesky` returns by default the upper-triangular matrix  $U = L'$ . `scipy.linalg.cholesky` can be made to return  $L$  using `scipy.linalg.cholesky(..., lower=True)`

## 1.1 Evaluating a multivariate normal log-likelihood function

Consider the multivariate normal density you learned in statistical methods course

$$y \sim \mathcal{N}(\mu, \Sigma), \quad \mu \in \mathbb{R}^n, \quad \Sigma \in \mathbb{R}^{n \times n}$$

Assuming  $\Sigma$  is p.d., the log-likelihood function is given by

$$-\frac{n}{2} \log(2\pi) - \frac{\log(\det(\Sigma))}{2} - \frac{1}{2} (y - \mu)' \Sigma^{-1} (y - \mu).$$

Here are some questions to consider:

- Suppose we know  $\mu$  and  $\Sigma$ , how do you evaluate the **red** part? (thinking about taking inverse?) Whenever we see matrix inverse, we should think in terms of solving linear equations. Consider using Cholesky decomposition.
- How about the **blue** part? Using the fact  $\log(\det(\Sigma)) = 2 \sum_{k=1}^n \log L_{kk}$ , why?

Therefore, consider Method 1 (for someone does not take this class): Compute  $\Sigma^{-1} \rightarrow$  Compute quadratic form  $\rightarrow$  Compute determinant

Consider Method 2 using Cholesky: 1) Do Cholesky decomposition  $\Sigma = LL'$ , 2) solve  $x : Lx = y - \mu$  by forward substitution, 3) compute quadratic form  $x'x$ ; 4) Compute determinant from Cholesky factor. How many flops for Method 1 & 2?

- Method 1: 1)  $2n^3/3$  flops; 2)  $O(n^2)$  flops; 3)  $2n^3/3 + O(n^2)$  flops  **$4n^3/3 + O(n^2) = \mathcal{O}(4n^3/3)$**
- Method 2: 1)  $n^3/3$  flops; 2)  $n^2$  flops; 3)  $O(n)$  flops; 4)  $O(n)$  flops  **$n^3/3 + n^2 + O(n) = \mathcal{O}(n^3/3)$**

Note: the forward substitution can be solve using

```
1 import scipy.linalg as slg
2 z = slg.solve_triangular(L, x-mu, lower=True)

1 z = forwardsolve(L, x-mu, lower=True)
```

Another function is backsolve.

Example <https://tomroth.com.au/decomp/>

## 1.2 Linear regression by Cholesky

The goal is to solve

$$X'X\beta = X'y$$

Assume  $X \in \mathbb{R}^{n \times p}$  is a full column rank matrix. It is easy to work with the **augmented matrix**

$$\begin{pmatrix} X'X & X'y \\ y'X & y'y \end{pmatrix} = \begin{pmatrix} L & 0 \\ \ell' & d \end{pmatrix} \times \begin{pmatrix} L' & \ell \\ 0' & d \end{pmatrix} = \begin{pmatrix} LL' & L\ell \\ \ell'L' & \ell'\ell + d^2 \end{pmatrix}$$

By Cholesky,  $X'X\beta = LL'\beta = X'y = L\ell$  and  $L'\beta = \ell$ . This solves  $\beta$  in  $p^2$  flops.

Next, since  $\ell = L^{-1}X'y$ , we have

$$\ell'\ell = yX(LL')^{-1}X'y = y'X(X'X)^{-1}X'y = y'P_xy = y'P_xP_xy = \hat{y}'\hat{y}$$

and

$$d^2 = y'y - \ell'\ell = y'(I - P_x)y = (y - \hat{y})'(y - \hat{y}) = SSE$$

We thus solved  $\beta$ ,  $\hat{y}$ , and  $SSE$  all altogether. In R: `chol2inv()` and in python: `cho_solve()`

Some notes: We only do inversion if standard errors are needed,  $(X'X)^{-1} = (LL')^{-1} = (L^{-1})'L^{-1}$

To summarize, how many flops for using Cholesky to solve linear regression?

- Form the lower triangular part of  $(X, y)'(X, y)$ :  **$n(p+1)^2/2$**  flops (why?)

- Cholesky decomposition of the augmented matrix,  $(p+1)^3/3$  flops
- Solve  $L'\beta = l$  for  $\hat{\beta}$ :  $p^2$  flops
- If need the standard error, estimate  $\hat{\sigma} = d^2/(n-p)$  and compute  $\hat{\sigma}^2(X'X)^{-1} = \hat{\sigma}^2(LL')^{-1}$ :  $2p^3/3$  flops

When  $n, p$  are large, total cost is  $O(p^3/3) + O(np^2/2)$  flops (without s.e.) and  $O(p^3) + O(np^2/2)$  flops (with s.e.).

What about using LU? The total flops is  $2p^3/3 + p^2 + np^2/2$  (without s.e.) and  $> 2p^3 + np^2/2$  (with s.e.)