Fall-2023 5304 LecN6 Notes

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Topics: PD; SPD; LDLT; Cholesky Factorization.

Math Tools: Inner Product, Eigenvalues and Eigencevectors, Properties of some special matrices

1 Positive Definite Matrices

Definition of PD

A real, square matrix is said to be PD if: $\langle Au, u \rangle > 0$ for all $u \neq 0$ and $u \in \mathbb{R}^n$

1.1 Properties

1, A is nonsingular.

This can be proof by contradiction.

2, The eigenvalues of A are real and positive.

This can be proved by the definition of eigenvalues.

2 Symmetric positive definite matrices, SPD

2.1 Definition of SPD

A square matrix is SPD iff it is **symmetric** and all its eigenvalues λ are **positive**, that is $\lambda > 0$.

Note: Don't forget the 2nd part of the definition, sometimes useful to think in this way.

Properties

1, Diagonal entries of SPD is positive.

Proof starting from the definition: Known that A is SPD, then for all nonzero vector u, we have $\langle Au, u \rangle > 0$. Then, utilize identity matrix to extract an element of A. (MV Product, dot product view). Good enough.

2, Each A_k is SPD

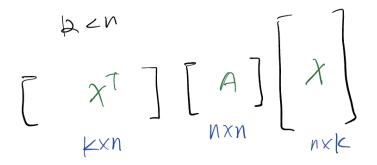
will fill this part later.

3, a conclusion

will fill this part later.

4, If A is SPD, then for any nxk matrix X of rank k, the matrix X^TAX is SPD.

Memory:



Proof (will use the notation of the inner product and def of SPD):

Application: Covariance Matrices in Statistics

3 Pred: SPD, Semi-Definite, Neg definite, and Indefinite Matrices

The LDL^T Factorization from LU

Theorem

Theorem. Let S be a positive-definite symmetric matrix. Then S has unique decompositions

$$S = LDL^T$$
 and $S = L_1L_1^T$

where:

- L is lower-unitriangular,
- D is diagonal with positive diagonal entries, and
- ullet L_1 is lower-triangular with positive diagonal entries.

For the LU Factorization, all we need is all A_k matrices for k=1 to n-1 have to be nonsingular. As A is SPD, implying that all A_k matrices from k=1 to n are nonsingular. Thus LU fac exists and is unique.

Inverse of a Diagonal Matrix is easy to compute:

Inverse of a Diagonal Matrix



$$D = \begin{bmatrix} d_1 & 0 & \cdots & 0 \\ 0 & d_2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & d_n \end{bmatrix} \qquad D^{-1} = \begin{bmatrix} 1/d_1 & 0 & \cdots & 0 \\ 0 & 1/d_2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & 1/d_n \end{bmatrix}$$

$$D^{-1} = \begin{bmatrix} 1/d_1 & 0 & \cdots & 0 \\ 0 & 1/d_2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & 1/d_n \end{bmatrix}$$

Nice results because of symmetry

Proof that $A = LU = LDL^T$

Thus, a SPD matrix A could be written in this form: $A = LDL^T$ where L is a lower triangular matrix with 1s on the diagonal, and D is a diagonal matrix (of U).

5 The Cholesky Factorization GGT from LDLT

GGT, scope of application: SPD matrices (??? what about semi-definte matrix???).

Diagonal of D shoud be positive so that we can take a square root to D to reach the Cholesky.

Remark. Suppose that S has an LDL^T decomposition with

$$D = \begin{pmatrix} d_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & d_n \end{pmatrix}.$$

Then we define

$$\sqrt{D} = \begin{pmatrix} \sqrt{d_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{d_n} \end{pmatrix},$$

so that $(\sqrt{D})^2 = D$, and we set $L_1 = L\sqrt{D}$. Then

$$L_1 L_1^T = L(\sqrt{D})(\sqrt{D})^T L^T = LDL^T = S,$$

so $L_1L_1^T$ is the Cholesky decomposition of S.

Proof: Diagonal of D shoud is positive

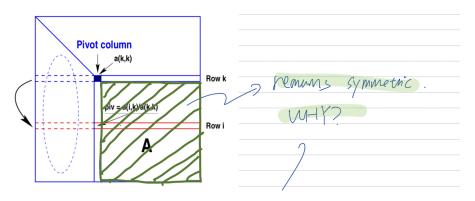
What can we say about G? G is lower triangular

The Cholesky: Any matrix that is SPD could be written as A = GGT where G is a lower triangular matrix, and positive entries on diagonal.

6 Algos of LDLT and GGT

row-oriented LDLT

Idea: Adapted from Gaussian but just work on upper part of the matrix because of symmetry because the working matrix A(k+1:n, k+1:n) in standard LU remains symmetric. See graph below:



Proof: A(k+1:n, k+1:n) is symmetric (induction argument).

What is the cost(FLOPs) of this algo?

Cost of standard LU:

Suppose k's index starting from 0, then in standard LU decomposition, when clearing the 1st col, each row replacement invoves n-1 multiplications (scale piv row) and n-1 substraction (update curr row), 2(n-1) flops in total. Hence, when k increase, problem size decrese, it takes $2(n-2)^2$ flops to clear the 2nd col etc.. Thus, we have:

Cost of LDLT (just half of LU): $\frac{1}{2}*\frac{2}{3}*n^3=\frac{1}{3}*n^3$

Rank 1 update: You're updating the matrix by something like uv^T where u and

v are the same.

- 2, row GGT, outer product form
- 3, column-oriented LDLT