

Convex Optimization: Reading Notes 5

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1 Triangular factorizations

Definition 1.1 (LU factorization). Let $A \in \mathbb{C}^{n \times n}$. A presentation $A = LU$, in which $L \in \mathbb{C}^{n \times n}$ is lower triangular and $U \in \mathbb{C}^{n \times n}$ is upper triangular, is called an LU factorization of A .

Theorem 1.2 (Row inclusion). Let $A \in \mathbb{C}^{n \times n}$ be given. A has an LU factorization in which L is nonsingular if and only if A has the row inclusion property: For each $i = 1, \dots, n-1$, $A[[i+1; 1, \dots, i]]$ is a linear combination of the rows of $A[[1, \dots, i]]$.

Here we use $A[[i+1; 1, \dots, i]]$ to denote the vector $[a_{(i+1)1} \ a_{(i+1)2} \ \dots \ a_{(i+1)i}]$, where $A = [a_{ij}]_{i,j=1}^n$.

Remark 1.3 (Leading principal submatrix). For $A \in \mathbb{C}^{n \times n}$, the i -th leading principal submatrix of A , denoted $A[[1, \dots, i]]$, is the submatrix obtained from A by deleting the last $n-i+1$ rows and columns.

The proof of Theorem 1.2 is as follows.

Proof. Suppose $A = LU \in \mathbb{C}^{n \times n}$ is the LU factorization with L nonsingular. First we show that $A[[n; 1, \dots, n-1]]$ is the linear combination of the rows of $A[[1, \dots, n-1]]$. Partition A, L and U as

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, \quad L = \begin{bmatrix} L_{11} & 0 \\ L_{21} & L_{22} \end{bmatrix}, \quad U = \begin{bmatrix} U_{11} & U_{12} \\ 0 & U_{22} \end{bmatrix},$$

where $A_{11}, L_{11}, U_{11} \in \mathbb{C}^{(n-1) \times (n-1)}$. Since $A = LU$, we have $A_{21} = L_{21}U_{11} = L_{21}L_{11}^{-1}L_{11}U_{11}$, and $A_{11} = L_{11}U_{11}$. Therefore $A_{21} = (L_{21}L_{11}^{-1})A_{11}$, which represents $A_{21} = A[[n; 1, \dots, n-1]]$ as the linear combination of the rows of $A[[1, \dots, n-1]]$. Moreover, since $A = LU$, for every $i = 1, \dots, n$ we have

$$A[[1, \dots, i]] = L[[1, \dots, i]]U[[1, \dots, i]].$$

Applying what we have obtained to this LU factorization of every leading principal submatrix of A verifies the row inclusion property.

Conversely, if A has the row inclusion property, we can construct an LU factorization inductively with L nonsingular. The cases $n = 1, 2$ are easily verified. Now suppose $A_{11} =$

$L_{11}U_{11}$, where L_{11} is nonsingular and $A_{11}, L_{11}, U_{11} \in \mathbb{C}^{(n-1) \times (n-1)}$. The row inclusion property gives that the row vector A_{21} is a linear combination of the rows of A_{11} , so there exists $y \in \mathbb{C}^{n-1}$ such that

$$A_{21} = y^T A_{11} = y^T L_{11} U_{11}.$$

From $A_{21} = L_{21}U_{11}$, we get $L_{21} = y^T L_{11}$. From $A_{12} = L_{11}U_{12}$ and that L_{11} is nonsingular, we obtain $U_{12} = L_{11}^{-1}A_{12}$. Let $L_{22} = 1$ and $U_{22} = A_{22} - L_{21}U_{12}$. In this way, we obtain an LU factorization of A , in which L is nonsingular, from the LU factorization of A_{11} . \square

Remark 1.4. *Similarly we can define the column inclusion property. A has an LU factorization with nonsingular U if and only if the column inclusion property holds. This follows from considering the LU factorization of A^T .*

Corollary 1.5. *Suppose that $A \in \mathbb{C}^{n \times n}$ and $\text{rank } A = k$. If $A[[1, \dots, j]]$ is nonsingular for all $j = 1, \dots, k$, then A has an LU factorization. Furthermore, either factor may be chosen to be unit triangular; both L and U are nonsingular if and only if $k = n$.*

Proof. For $A \in \mathbb{C}^{n \times n}$ with $\text{rank } A = k$ such that $A[[1, \dots, j]]$ is nonsingular for all $j = 1, \dots, k$, we first verify that A has both the row inclusion and column inclusion properties. For $j = 1, \dots, k$, since $A[[1, \dots, j]]$ is nonsingular, the rows of $A[[1, \dots, j]]$ are linearly independent, so they span \mathbb{C}^j and $A[[j+1; 1, \dots, j]]$ is certainly in it. For $j > k$, since $\text{rank } A = k$, the rows of $A[[1, \dots, j]]$ must span \mathbb{C}^j , and $A[[j+1; 1, \dots, j]]$ is in it. This shows the row inclusion property, and similarly the column inclusion property also holds. From Theorem 1.2 and Remark 1.4 it follows that A has an LU factorization where either L or U may be nonsingular.

Suppose $A = LU$ and L is nonsingular, which means that L has nonzero diagonal elements $\ell_{11}, \ell_{22}, \dots, \ell_{nn}$. Let $D = \text{diag}(\ell_{11}, \dots, \ell_{nn})$ which is nonsingular, and let $L = L'D$ so that L' is unit lower triangular. Note that $U' = DU$ is still upper triangular, so we obtain a new LU factorization of $A = L'U'$ in which the left factor is unit triangular. Similarly, the right factor could also be unit triangular.

For $k = n$, the matrix A is nonsingular, so the other factor must be nonsingular if either factor is nonsingular. Conversely, for both L and U nonsingular, $A = LU$ is nonsingular, and therefore has full rank. \square

Corollary 1.6 (LDU factorization). *Let $A = [a_{ij}] \in \mathbb{C}^{n \times n}$ be given. Suppose that the leading principal submatrix $A[[1, \dots, i]]$ is nonsingular for all $i = 1, \dots, n$. Then $A = LDU$, in which $L, D, U \in \mathbb{C}^{n \times n}$, L is unit lower triangular, U is unit upper triangular, $D = \text{diag}(d_1, \dots, d_n)$ is diagonal, $d_1 = a_{11}$, and*

$$d_i = \frac{\det A[[1, \dots, i]]}{\det A[[1, \dots, i-1]]}.$$

The factors L, D and U are uniquely determined.

Proof. From Corollary 1.5, A must have an LU factorization $A = L'U'$ where both L' and U' are nonsingular. It is easy to find unit triangular L and U such that $L' = LD_1$ and $D_2U = U'$,

where D_1 and D_2 are diagonal. Then A has an LDU factorization $A = LDU$, $D = D_1D_2$, and

$$\det A [[1, \dots, i]] = \det D [[1, \dots, i]] = \prod_{j=1}^i d_j, \quad i = 1, \dots, n.$$

So $d_1 = a_{11}$, and

$$d_i = \frac{\det A [[1, \dots, i]]}{\det A [[1, \dots, i-1]]}, \quad i = 2, \dots, n.$$

The uniqueness of L and U could be proved inductively. \square

Lemma 1.7. *Let $A \in \mathbb{C}^{n \times n}$ be nonsingular. Then there is a permutation matrix $P \in \mathbb{C}^{n \times n}$ such that $\det((P^T A) [[1, \dots, j]]) \neq 0$ for $j = 1, \dots, n$.*

Proof. Prove by induction on n . The cases $n = 1, 2$ are trivial. Suppose that such matrix exists for cases $1, 2, \dots, n-1$. For a nonsingular $A \in \mathbb{C}^{n \times n}$, we delete its last column, and the remaining $n-1$ columns are linearly independent and hence they contain $n-1$ linearly independent rows. Permute these rows to be the first $n-1$ rows, and then apply the induction hypothesis to the nonsingular $(n-1) \times (n-1)$ leading principal submatrix. This determines a desired permutation P , and $P^T A$ is nonsingular. \square

Theorem 1.8 (PLU factorization). *For each $A \in \mathbb{C}^{n \times n}$ there is a permutation matrix $P \in \mathbb{C}^{n \times n}$, a unit lower triangular $L \in \mathbb{C}^{n \times n}$ and an upper triangular $U \in \mathbb{C}^{n \times n}$ such that $A = PLU$.*

Proof. It suffices to show that there exists a permutation matrix Q such that QA has the row inclusion property, and thus has an LU factorization $QA = LU$. Let $P = Q^T$ and we have $A = PLU$.

If A is nonsingular, the desired permutation matrix is guaranteed by Lemma 1.7. Suppose A is singular, with $\text{rank } A = k < n$. First we permute the rows of A so that the first k rows are linearly independent. This gives that $A [[i+1; 1, \dots, i]]$ is a linear combination of the rows of $A [[1, \dots, i]]$ for $i = k, \dots, n-1$. If $A [[1, \dots, k]]$ is nonsingular, apply Lemma 1.7 again to $A [[1, \dots, k]]$ so that the row inclusion property holds for $A [[1, \dots, k]]$, and thus holds for A . If $A [[1, \dots, k]]$ is singular, apply the same procedure recursively to $A [[1, \dots, k]]$ until either the upper left block is 0, or it is nonsingular. Hence the desired permutation matrix exists. \square

Theorem 1.9 (LPU factorization). *For every $A \in \mathbb{C}^{n \times n}$, there exists a permutation matrix $P \in \mathbb{C}^{n \times n}$, a unit lower triangular matrix $L \in \mathbb{C}^{n \times n}$ and an upper triangular matrix $U \in \mathbb{C}^{n \times n}$ such that $A = LPU$. Moreover, the factor P is uniquely determined if A is nonsingular.*

Theorem 1.9 could be proved by induction. The proof is omitted here.

Theorem 1.10 (LPDU factorization). *For each nonsingular $A \in \mathbb{C}^{n \times n}$, there is a unique permutation matrix P , a unique nonsingular diagonal matrix D , a unit lower triangular matrix L , and a unit upper triangular matrix U such that $A = LPDU$.*

Proof. Theorem 1.9 guarantees the existence of a unique permutation matrix P , a unit lower triangular matrix L and a nonsingular upper triangular matrix U' such that $A = LPU'$. Let $D = \text{diag}(\text{diag}(U'))$ so that $U' = DU$, where U is unit upper triangular. This shows the existence.

To show the uniqueness of D , we assume there exists another diagonal matrix D_1 , unit lower triangular L_1 and unit upper triangular U_1 such that $A = L_1PD_1U_1$. Since $A = LPDU$, we have $LPDU = L_1PD_1U_1$, and thus

$$P^T L_1^{-1} L P D = D_1 U_1 U^{-1}.$$

Since the unit lower/upper triangular matrices form a multiplicative group, the main diagonal entries of $L_1^{-1}L$ and U_1U^{-1} are all ones. Since P is a permutation matrix, it is clear that the main diagonal entries of $P^T(L_1^{-1}L)P$ are also all ones. Hence $D = D_1$. \square

2 Cholesky factorization

Theorem 2.1 (Cholesky factorization). *Let $A \in \mathbb{S}^n$ be given. A is positive definite if and only if there exists a lower triangular matrix L with positive diagonal elements such that $A = LL^T$. Such L is unique and is called the Cholesky factor of A .*

Proof. \Leftarrow : Suppose $A = LL^T$ in which L is lower triangular with positive diagonal elements. It follows immediately that A is positive semidefinite. Since the diagonal elements of L are all positive, L and L^T are nonsingular, so $A = LL^T$ is nonsingular, and thus positive definite.

\Rightarrow : We will show the existence of the Cholesky factor L by induction on n . The case $n = 1$ is trivial. Suppose this is true up to $n - 1$, and for $A \in \mathbb{S}^n$, write

$$A = \begin{bmatrix} \alpha & b^T \\ b & A' \end{bmatrix}, \quad A' \in \mathbb{R}^{(n-1) \times (n-1)}.$$

Decompose this in the form

$$A = \begin{bmatrix} 1 & 0 \\ \frac{1}{\alpha}b & I_{n-1} \end{bmatrix} \begin{bmatrix} \alpha & 0 \\ 0 & A' - \frac{bb^T}{\alpha} \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\alpha}b^T \\ 0 & I_{n-1} \end{bmatrix},$$

where $\Delta_A = A' - \frac{bb^T}{\alpha}$ is the *Schur complement* of A . Since A is positive definite, it follows that the Schur complement Δ_A is also positive definite. By induction hypothesis there exists a lower triangular matrix L_Δ with positive diagonal elements such that $\Delta_A = L_\Delta L_\Delta^T$. Therefore

$$\begin{aligned} A &= \begin{bmatrix} 1 & 0 \\ \frac{1}{\alpha}b & I_{n-1} \end{bmatrix} \begin{bmatrix} \alpha & 0 \\ 0 & L_\Delta L_\Delta^T \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\alpha}b^T \\ 0 & I_{n-1} \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 \\ \frac{1}{\alpha}b & I_{n-1} \end{bmatrix} \begin{bmatrix} \sqrt{\alpha} & 0 \\ 0 & L_\Delta \end{bmatrix} \begin{bmatrix} \sqrt{\alpha} & 0 \\ 0 & L_\Delta^T \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\alpha}b^T \\ 0 & I_{n-1} \end{bmatrix} \\ &= \begin{bmatrix} \sqrt{\alpha} & 0 \\ \frac{1}{\sqrt{\alpha}}b & L_\Delta \end{bmatrix} \begin{bmatrix} \sqrt{\alpha} & \frac{1}{\sqrt{\alpha}}b^T \\ 0 & L_\Delta^T \end{bmatrix} = LL^T, \end{aligned}$$

where $L = \begin{bmatrix} \sqrt{\alpha} & 0 \\ \frac{1}{\sqrt{\alpha}}\mathbf{b} & L_{\Delta} \end{bmatrix}$ is lower-triangular with positive diagonal elements. This shows the existence.

To prove the uniqueness, suppose $A = LL^T = KK^T$, where K is also a Cholesky factor of A . Then $K^{-1}L = K^T(L^T)^{-1}$. Since the nonsingular lower triangular matrices form a group, $K^{-1}L$ is lower triangular and $K^T(L^T)^{-1}$ is upper triangular. Therefore $K^{-1}L = D$ for some diagonal matrix D . For real matrices, take this into $A = LL^T = KK^T$ and we obtain $KDD^TK^T = KK^T$, which gives $DD^T = I$, so $D = I$. The uniqueness also holds for complex matrices, but the proof is omitted here. \square

Remark 2.2. From the proof above, we also obtain a Cholesky factorization algorithm. To find the Cholesky factor of $A \in \mathbb{S}_{++}^n$, we only need to compute $\Delta_A = A' - \frac{1}{\alpha}\mathbf{b}\mathbf{b}^T$, where

$$A = \begin{bmatrix} \alpha & \mathbf{b}^T \\ \mathbf{b} & A' \end{bmatrix},$$

which involves n^2 flops (for computing $\mathbf{b}\mathbf{b}^T$), and then recursively find the Cholesky factorization of $\Delta_A \in \mathbb{S}_{++}^{n-1}$. So the total number of flops is approximately

$$\sum_n n^2 = \frac{1}{3}n^3.$$

3 Matrix inversion lemma

There are many different versions of the matrix inversion lemma. The *Sherman-Morrison formula* gives that

$$(A + \mathbf{u}\mathbf{v}^T)^{-1} = A^{-1} - \frac{A^{-1}\mathbf{u}\mathbf{v}^T A^{-1}}{1 + \mathbf{v}^T A^{-1}\mathbf{u}},$$

where A is invertible matrix, $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$, $1 + \mathbf{v}^T A^{-1}\mathbf{u} \neq 0$ and $A + \mathbf{u}\mathbf{v}^T$. The *Sherman-Morrison-Woodbury formula* deals with the case of two matrices and gives that

$$(D + \mathbf{W}\mathbf{V}^T)^{-1} = D^{-1} - D^{-1}\mathbf{V}(\mathbf{I} + \mathbf{V}^T D^{-1}\mathbf{V})^{-1}\mathbf{V}^T D^{-1}.$$

However, the most generalized version is as follows.

Theorem 3.1. Suppose A, B, C, D are matrices, vectors or numbers, such that $A + BCD$ exists. Suppose $A, C, C^{-1} + DA^{-1}B$ are invertible. Then $A + BCD$ is invertible and

$$(A + BCD)^{-1} = A^{-1} - A^{-1}B(C^{-1} + DA^{-1}B)^{-1}DA^{-1}.$$

The proof involves nothing but fundamental operations of matrices.

4 Condition number

The condition number associated with a linear equation $\mathbf{A}\mathbf{x} = \mathbf{b}$ gives a bound on how inaccurate the solution \mathbf{x} will be after approximation. Let \mathbf{e} be the error in \mathbf{b} . Assuming that \mathbf{A} is a nonsingular matrix, the error in the solution $\mathbf{A}^{-1}\mathbf{b}$ is $\mathbf{A}^{-1}\mathbf{e}$. Then the ratio of the relative error in the solution to the relative error in \mathbf{b} is.

$$\frac{\|\mathbf{A}^{-1}\mathbf{e}\| / \|\mathbf{A}^{-1}\mathbf{b}\|}{\|\mathbf{e}\| / \|\mathbf{b}\|} = \frac{\|\mathbf{A}^{-1}\mathbf{e}\|}{\|\mathbf{e}\|} \cdot \frac{\|\mathbf{b}\|}{\|\mathbf{A}^{-1}\mathbf{b}\|}.$$

The maximum value of the above when $\mathbf{e}, \mathbf{b} \neq 0$ is

$$\begin{aligned} \max_{\mathbf{e}, \mathbf{b} \neq 0} \frac{\|\mathbf{A}^{-1}\mathbf{e}\|}{\|\mathbf{e}\|} \cdot \frac{\|\mathbf{b}\|}{\|\mathbf{A}^{-1}\mathbf{b}\|} &= \max_{\mathbf{e} \neq 0} \frac{\|\mathbf{A}^{-1}\mathbf{e}\|}{\|\mathbf{e}\|} \max_{\mathbf{b} \neq 0} \frac{\|\mathbf{b}\|}{\|\mathbf{A}^{-1}\mathbf{b}\|} \\ &= \max_{\mathbf{e} \neq 0} \frac{\|\mathbf{A}^{-1}\mathbf{e}\|}{\|\mathbf{e}\|} \max_{\mathbf{x} \neq 0} \frac{\|\mathbf{A}\mathbf{x}\|}{\|\mathbf{x}\|} \\ &= \|\mathbf{A}^{-1}\| \|\mathbf{A}\|, \end{aligned}$$

where $\|\cdot\|$ is the matrix norm associated with the vector norm $\|\cdot\|$. If $\|\cdot\|$ is the Euclidean norm, then

$$\|\mathbf{A}^{-1}\| \|\mathbf{A}\| = \frac{\sigma_{\max}(\mathbf{A})}{\sigma_{\min}(\mathbf{A})}.$$

Definition 4.1 (Condition number of matrices). *The condition number of a matrix \mathbf{A} is defined as*

$$\kappa(\mathbf{A}) = \begin{cases} \frac{\sigma_{\max}(\mathbf{A})}{\sigma_{\min}(\mathbf{A})}, & \mathbf{A} \text{ is nonsingular,} \\ \infty, & \mathbf{A} \text{ is singular.} \end{cases}$$

Definition 4.2 (Width of convex sets). *The width of a convex set $C \subseteq \mathbb{R}^n$ in the direction \mathbf{q} , where $\|\mathbf{q}\|_2 = 1$, is defined as*

$$W(C, \mathbf{q}) = \sup_{z \in C} \mathbf{q}^T z - \inf_{z \in C} \mathbf{q}^T z.$$

Definition 4.3 (Minimum and maximum width). *The minimum width and maximum width of a convex set $C \subseteq \mathbb{R}^n$ are given by*

$$W_{\min} = \inf_{\|\mathbf{q}\|_2=1} W(C, \mathbf{q}), \quad W_{\max} = \sup_{\|\mathbf{q}\|_2=1} W(C, \mathbf{q}).$$

Definition 4.4 (Condition number of convex sets). *The condition number of a convex set $C \subseteq \mathbb{R}^n$ is defined as*

$$\mathbf{cond}(C) = \frac{W_{\max}^2}{W_{\min}^2}.$$

Let $C_\alpha = \{\mathbf{x} \mid f(\mathbf{x}) \leq \alpha\}$ be the α -sublevel set. Suppose there exist constants m and M such that $m\mathbf{I} \preceq \nabla^2 f(\mathbf{x}) \preceq M\mathbf{I}$. Then

$$p^* + \frac{M}{2} \|\mathbf{y} - \mathbf{x}^*\|_2^2 \geq f(\mathbf{y}) \geq p^* + \frac{m}{2} \|\mathbf{y} - \mathbf{x}^*\|_2^2.$$

This shows that $B_{\text{inner}} \subseteq C_\alpha \subseteq B_{\text{upper}}$, where

$$B_{\text{inner}} = \left\{ \mathbf{y} \mid \|\mathbf{y} - \mathbf{x}^*\|_2 \leq \sqrt{2(\alpha - \mathbf{p}^*)/M} \right\},$$

$$B_{\text{outer}} = \left\{ \mathbf{y} \mid \|\mathbf{y} - \mathbf{x}^*\|_2 \leq \sqrt{2(\alpha - \mathbf{p}^*)/m} \right\}.$$

Therefore

$$\mathbf{cond}(C_\alpha) \leq \frac{M}{m}.$$

From the Taylor's formula we can also see that

$$f(\mathbf{y}) \approx \mathbf{p}^* + \frac{1}{2} (\mathbf{y} - \mathbf{x}^*)^\top \nabla^2 f(\mathbf{x}^*) (\mathbf{y} - \mathbf{x}^*),$$

so for α close to \mathbf{p}^* ,

$$C_\alpha \approx \left\{ \mathbf{y} \mid (\mathbf{y} - \mathbf{x}^*)^\top \nabla^2 f(\mathbf{x}^*) (\mathbf{y} - \mathbf{x}^*) \leq 2(\alpha - \mathbf{p}^*) \right\},$$

which is an ellipsoid with center \mathbf{x}^* . Therefore

$$\lim_{\alpha \rightarrow \mathbf{p}^*} \mathbf{cond}(C_\alpha) = \kappa(\nabla^2 f(\mathbf{x}^*)).$$