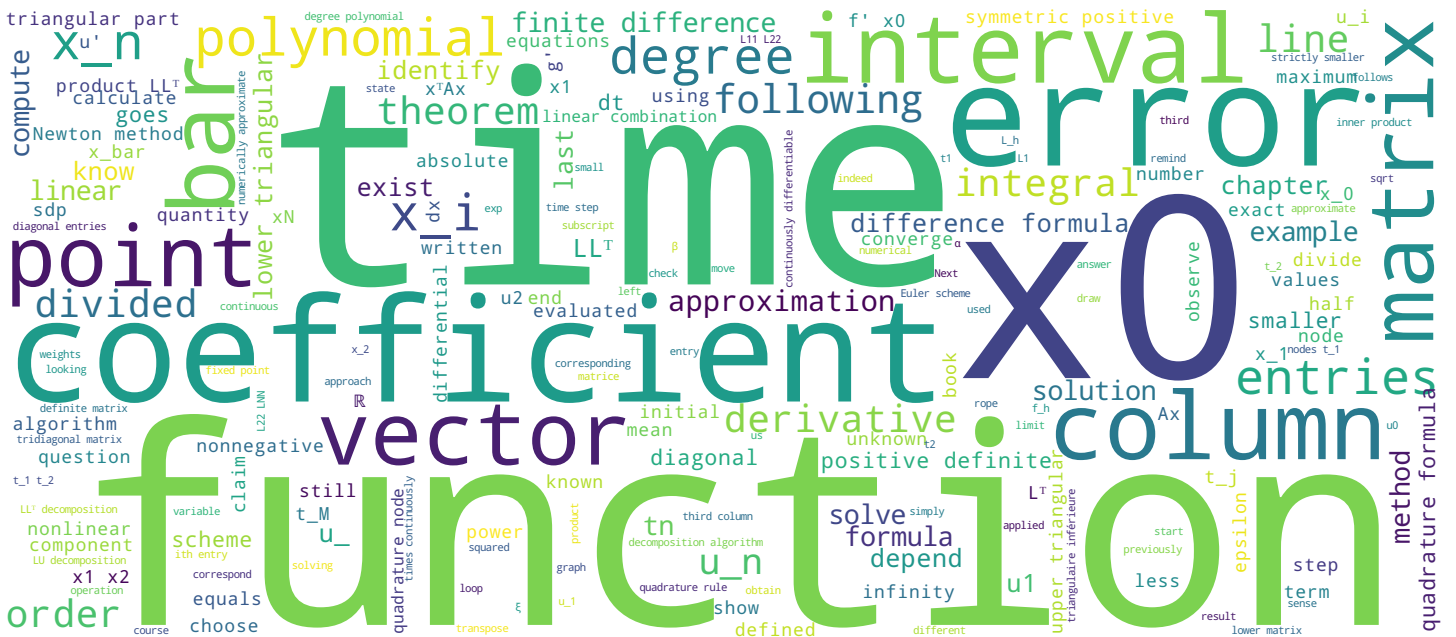


Chap 5: Decomposition LL^T (Cholesky)



Video



Chap 5 : Décomposition LL^T (Cholesky)

Def: A $N \times N$ matrice est symétrique définie positive si (sdp)

- $A = A^T$ ($a_{ij} = a_{ji}$ $1 \leq i, j \leq N$)

- $\forall \vec{x} \in \mathbb{R}^N \quad \vec{x}^T A \vec{x} \geq 0 \quad \vec{x}^T A \vec{x} = (\vec{x}, A\vec{x}) = \sum_{i=1}^N x_i (A\vec{x})_i = \sum_{i,j=1}^N a_{ij} x_i x_j$

- $\vec{x}^T A \vec{x} = 0 \Leftrightarrow \vec{x} = \vec{0}$

Si A est sdp alors il existe L ($l_{ii} > 0$) tq $A = LL^T$ L

Let's move to the LL^T decomposition, also called Cholesky decomposition, which is applied in the case where the matrix A is a symmetric positive definite matrix. First of all, let's give a definition. Let A be a $N \times N$ matrix. This matrix is symmetric positive definite, if the three following conditions are met. First, A is symmetric, $A = A^T$ (transpose of A) in the sense where the entries $a_{ij} = a_{ji}$ for all i, j between 1 and N. Second condition: if I take any vector x in \mathbb{R}^N , and compute $x^T A x$, then this quantity is always positive or 0. Let me remind you that here, $x^T A x$ is the same as the inner product between x and Ax , that is, the sum for i from 1 to N, of the i th entry of the vector x with the i th entry of the vector Ax , which is the sum over all the subscripts i, j from 1 to N, so the sum over i , from 1 to N, sum over j from 1 to N of $a_{ij} x_i x_j$. Thus the second condition is that $x^T A x$ is nonnegative. c'est un scalaire. And the last condition, $x^T A x = 0$ if and only if x is the 0 vector. So if A is a symmetric definite positive matrix, we will abbreviate symmetric positive definite with "sdp", if A is sdp, then we can show that there exists a unique decomposition $A = LL^T$, so there exists a lower matrix L, with diagonal entries L_{ii} that are strictly positive, such that $A = LL^T$, again L is lower triangular.

Notes

Summary



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Si A est sdp alors il existe L ($l_{ii} > 0$) tq $A = LL^T$ L triang. inf.

$$\begin{array}{|c|c|c|}
 \hline
 \begin{array}{ccc} a_{11} & \dots & a_{1N} \\ \vdots & & \vdots \\ a_{N1} & \dots & a_{NN} \end{array} & = & \begin{array}{ccc} l_{11} & & (0) \\ \vdots & \ddots & \vdots \\ l_{N1} & \dots & l_{NN} \end{array} \\
 A & & L
 \end{array}
 \quad
 \begin{array}{ccc} l_{11} & \dots & l_{1N} \\ \vdots & & \vdots \\ (0) & \dots & l_{NN} \end{array}$$

L^T

On identifie les coeff de A et LL^T dans l'ordre suivant

Donc triangulaire inférieure, *lower metrics* en anglais. I can draw the following. Here is the matrix A, with entries a_{11}, \dots, a_{1N} on the first line, a_{11}, \dots, a_{N1} on the first column, until a_{NN} . If A is sdp, this matrix, can be written as the product of L which is a lower matrix, since it is lower triangular, it has coefficients $L_{11}, L_{22}, \dots, L_{NN}$, that are strictly positive. The upper triangular part has only zeroes, and here we have the coefficient L_{N1} , and so on. And then L^T is the transposed of L. Donc transposé. The diagonal entries are the same, $L_{11}, L_{22}, \dots, L_{NN}$. La partie triangulaire supérieure qui avait des coefficients nuls se retrouve dans la partie, cette fois-ci, triangulaire inférieure. So the lower part of L^T has only 0's, And here are the coefficients L_{N1} , and so on. To get the Cholesky (or LL^T) decomposition algorithm we need to do half the operations needed for the LU decomposition algorithm. So we identify the coefficients as before. We identify the entries of A and LL^T in the following order : As before, when I identify all the entries of the first column of A with the entries of the first column of the product LL^T , I will get all the coefficients of the first column of L.

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- $\forall \vec{x} \in \mathbb{R}^N$ $\vec{x}^T A \vec{x} \geq 0$ $\vec{x}^T A \vec{x} = (\vec{x}, A \vec{x}) = \sum_{i=1}^N x_i (A \vec{x})_i = \sum_{i,j=1}^N a_{ij} x_i x_j$

- $\vec{x}^T A \vec{x} = 0 \Leftrightarrow \vec{x} = \vec{0}$

Si A est sdp alors il existe L ($l_{ii} > 0$) tq $A = LL^T$ L triang. inf.

$$\begin{array}{|c|c|c|} \hline a_{11} & \dots & a_{1N} \\ \hline \vdots & \ddots & \vdots \\ \hline a_{N1} & \dots & a_{NN} \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline l_{11} & \dots & 0 \\ \hline \vdots & \ddots & \vdots \\ \hline l_{N1} & \dots & l_{NN} \\ \hline \end{array} \begin{array}{|c|c|c|} \hline l_{11} & \dots & l_{N1} \\ \hline 0 & \ddots & 0 \\ \hline 0 & \dots & l_{NN} \\ \hline \end{array}$$

$A \qquad \qquad \qquad L \qquad \qquad \qquad L^T$

On identifie les coeff de A et LL^T dans l'ordre suivant

This time I can directly identify the coefficients of the second column of A with the coefficients of the second column of the product LL^T to get the coefficients of the second column of L. We do half the work, and so on. If I take the third column, I will get the coefficients of the third column of LL^T and in the end, I will have identified all the entries, say, half of the coefficients of A, the lower triangular part with the coefficients of the product LL^T , and I will have all the coefficients of L, and so, since L^T is the transpose of L, we have all the entries of L and L^T . We'll now consider the algorithm in the case of a tridiagonal matrix.

Notes

Summary

